

"Pine_River_Dam",0.0237,-0.0181,0.0654,0
"Pipestone",0.0615,0.0139,0.1092,1
"Pokegama_Dam",0.0092,-0.0418,0.0601,0
"Red_Lake_Indian_Agency",-0.0232,-0.1121,0.0657,0
"Redwodd_Falls",0.0908,0.0266,0.1551,1
"St_Cloud",0.0326,-0.0644,0.1296,0
"St_Paul",0.0237,-0.1065,0.1539,0
"St_Peter",0.0714,0.0062,0.1366,1
"St_Vincent",0.0851,0.0178,0.1525,1
"Tower",0.0146,-0.0846,0.1138,0
"Warroad",0.113,0.0481,0.1779,1
"Winnibigoshish",0.0071,-0.0686,0.0828,0
"Winona",0.1312,0.0852,0.1771,1
"Coastal",1.4568,0.7335,2.1801,1
"Inland",1.863,0.5719,3.1541,1
"All",3.3198,1.5461,5.0936,1

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY", 0.1818, 0.0146, 0.3491, 1
"Boston MA", -0.0298, -0.1698, 0.1102, 0
"Portland ME", 0.1169, 0.0232, 0.2107, 1
"Gardiner ME", 0.0993, -0.066, 0.2646, 0
"Albany NY", 0.1163, 0.0227, 0.2098, 1
"Concord NH", 0.1299, -0.0046, 0.2645, 0
"Montreal Q", 0.0933, 0.0108, 0.1758, 1
"Lakeport NH", 0.1985, 0.0782, 0.3187, 1
"Burlington VT", 0.0973, 0.0346, 0.16, 1
"Cornwall VT", 0.1233, 0.0548, 0.1918, 1
"Northfield VT", 0.1472, 0.0547, 0.2398, 1
"Corinth VT", 0.1501, 0.0397, 0.2605, 1
"Hanover NH", 0.0843, 0.0076, 0.161, 1
"Rochester NY", 0.0779, 0.018, 0.1377, 1
"Buffalo NY", 0.0801, 0.0011, 0.1592, 1
"Middletown CT", -0.0486, -0.2177, 0.1206, 0
"Ithaca NY", 0.0774, 0.0277, 0.1271, 1
"Amherst MA", 0.1158, 0.0358, 0.1957, 1
"Setauket Strong NY", 0.144, 0.0354, 0.2526, 1
"Fitchburg MA", -0.0412, -0.1795, 0.0971, 0
"Providence RI", 0.0902, -0.0012, 0.1817, 0
"Waterville ME", 0.0708, -0.0295, 0.1712, 0
"Lowville NY", 0.0576, -0.0104, 0.1255, 0
"Cooperstown NY", 0.2333, 0.0988, 0.3677, 1
"Berlin NH", 0.1231, 0.0508, 0.1954, 1
"Farmington ME", 0.095, -0.0273, 0.2174, 0
"Eastport ME", 0.1473, -0.0267, 0.3214, 0
"Coastal", 1.1527, 0.2881, 2.0173, 1
"Inland", 1.5784, 0.4456, 2.7113, 1
"All", 2.7312, 0.8221, 4.6403, 1

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Blaine"	0.0421	-0.0233	0.1075	0
"Bellingham"	-0.0134	-0.0617	0.0349	0
"Quil"	-0.0035	-0.179	0.172	0
"Clearwater"	-0.2207	-0.4924	0.0511	0
"Aberdeen"	0.0104	-0.11	0.1309	0
"Raymond"	-0.1006	-0.3212	0.12	0
"Astoria"	-0.0413	-0.3094	0.2267	0
"Tillamook"	-0.07	-0.2152	0.0752	0
"Newport"	-0.3545	-0.5852	-0.1239	1
"Florence"	-0.0365	-0.1704	0.0974	0
"North Bend"	0.0479	-0.1383	0.2342	0
"Bandon"	-0.0752	-0.1859	0.0355	0
"Port"	-0.1145	-0.2505	0.0216	0
"Crescent City"	-0.0034	-0.1822	0.1754	0
"Eureka"	-0.0148	-0.1455	0.1158	0
"Upper Mattole"	-0.0834	-0.3304	0.1636	0
"Fort Bragg"	0.0327	-0.0925	0.1578	0
"Ukiah"	-0.0801	-0.2276	0.0674	0
"Healdsburg"	-0.0637	-0.1964	0.0689	0
"San Francisco"	0.0282	-0.0718	0.1281	0
"Santa Cruz"	0.0018	-0.0984	0.1019	0
"Big Sur"	0.0137	-0.1386	0.1659	0
"Paso Robles"	0.0238	-0.0293	0.0768	0
"Santa Maria"	0.012	-0.0674	0.0913	0
"Santa Barbara"	0.0163	-0.0816	0.1141	0
"Los Angeles"	0.0047	-0.0917	0.1011	0
"Santa Ana"	-0.0088	-0.1051	0.0875	0
"Escondido"	0.0027	-0.1	0.1054	0
"San Diego"	0.013	-0.0607	0.0868	0
"Coastal"	-0.4133	-1.4659	0.6393	0
"Inland"	-0.622	-1.7073	0.4633	0
"All"	-1.0354	-3.1421	1.0713	0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	0.0841	0.0002	0.168	1
"Galveston"	0.1429	0.02	0.2658	1
"Shreveport"	0.1425	-0.0242	0.3091	0
"Vicksburg"	0.0628	-0.1857	0.3112	0
"New Orleans"	0.0673	-0.0808	0.2153	0
"Memphis"	0.104	-0.003	0.211	0
"Mobile"	0.0433	-0.0664	0.1529	0
"Nashville"	0.0595	-0.0667	0.1857	0
"Montgomery"	0.0653	-0.1471	0.2777	0
"Atlanta"	0.082	-0.0367	0.2008	0
"Knoxville"	0.1169	0.0027	0.2312	1
"Macon"	0.0634	-0.0127	0.1396	0
"Quitman"	-0.0007	-0.1603	0.1589	0
"Augusta"	0.0748	-0.062	0.2115	0
"Key West"	0.0397	-0.0467	0.126	0
"Jacksonville"	0.0385	-0.0636	0.1406	0
"Lenoir"	0.0555	-0.0883	0.1993	0
"Savannah"	-0.0517	-0.1499	0.0464	0
"Charleston"	0.0447	-0.0894	0.1788	0
"Lynchburg"	0.0859	-0.0078	0.1795	0
"Wilmington"	0.1354	0.0369	0.234	1
"Weldon"	0.1454	0.0265	0.2642	1
"Washington"	0.0695	-0.0326	0.1716	0
"Norfolk"	0.0958	-0.0005	0.1922	0
"Coastal"	0.5559	0.0449	1.0668	1
"Inland"	1.2108	0.173	2.2486	1
"All"	1.7667	0.2716	3.2617	1

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.1938, 0.0696, 0.318, 1
 "Milwaukee WI", -0.0001, -0.2083, 0.2081, 0
 "Green Bay WI", 0.1627, -0.0012, 0.3266, 0
 "Chippewa Falls WI", 0.1053, -0.042, 0.2525, 0
 "Medford WI", 0.0798, -0.1387, 0.2983, 0
 "Dubuque IA", 0.1122, -0.0908, 0.3153, 0
 "Des Moines IA", -0.0138, -0.2278, 0.2002, 0
 "Cedar Rapids IA", 0.0465, -0.1123, 0.2053, 0
 "Davenport IA", 0.1148, -0.0755, 0.3052, 0
 "Sioux City IA", 0.0843, -0.0788, 0.2474, 0
 "Aurora IL", 0.0818, -0.0956, 0.2592, 0
 "Denison IA", 0.0371, -0.1881, 0.2623, 0
 "Spencer IA", 0.1055, -0.1785, 0.3894, 0
 "Fort Dodge IA", 0.0043, -0.2009, 0.2096, 0
 "Rockford IL", 0.0665, -0.0679, 0.2009, 0
 "Sioux Falls SD", 0.0909, -0.035, 0.2168, 0
 "Charles City IA", 0.144, -0.068, 0.356, 0
 "Hillsboro WI", 0.1965, 0.026, 0.3669, 1
 "Stevens Point WI", 0.125, -0.056, 0.3059, 0
 "Iron Mountain MI", 0.0856, -0.0527, 0.2239, 0
 "Park Falls WI", 0.1145, -0.1155, 0.3446, 0
 "Ashland WI", -0.1146, -0.2948, 0.0657, 0
 "Hancock-Houghton AP MI", -0.2287, -0.7099, 0.2526, 0
 "Oshkosh WI", 0.1363, -0.1102, 0.3828, 0
 "Shawano WI", 0.1165, -0.0927, 0.3257, 0
 "Spooner WI", -0.044, -0.194, 0.106, 0
 "Grundy Center IA", 0.0573, -0.1459, 0.2606, 0
 "Lansing IA", 0.181, -0.0025, 0.3646, 0
 "Rhineland WI", 0.1452, -0.0252, 0.3156, 0
 "Bergland Dam MI", 0.1042, -0.0478, 0.2563, 0
 "Alexandria", -0.0386, -0.2347, 0.1575, 0
 "Beardsley", 0.0763, -0.0833, 0.236, 0
 "Canby", 0.0461, -0.0727, 0.165, 0
 "Crookston", -0.0425, -0.2206, 0.1356, 0
 "Duluth", -0.0051, -0.0926, 0.0824, 0
 "Fairmont", -0.0618, -0.2427, 0.1191, 0
 "Farmington", 0.1346, -0.0675, 0.3366, 0
 "Fergus_Falls", 0.1404, 0.0011, 0.2797, 1
 "Grand_Meadow", 0.1059, -0.0206, 0.2324, 0
 "Grand_Portage", 0.1835, 0.0938, 0.2732, 1
 "Hinckley", 0.0567, -0.1428, 0.2562, 0
 "International_Falls", 0.1075, 0.0379, 0.177, 1
 "Leech_Lake", 0.0002, -0.0928, 0.0932, 0
 "Little_Falls", 0.1319, -0.0277, 0.2915, 0
 "Montevideo", 0.033, -0.1271, 0.193, 0
 "Moorhead", 0.0753, -0.3014, 0.452, 0
 "Morris", 0.0093, -0.0873, 0.1058, 0
 "Park_Rapids", -0.1664, -0.2612, -0.0717, 1

"Pine_River_Dam",-0.0114,-0.094,0.0713,0
"Pipestone",0.0385,-0.1067,0.1837,0
"Pokegama_Dam",-0.0469,-0.1612,0.0674,0
"Red_Lake_Indian_Agency",-0.1056,-0.2871,0.076,0
"Redwodd_Falls",0.0784,-0.1324,0.2892,0
"St_Cloud",0.0928,-0.1185,0.304,0
"St_Paul",-0.0975,-0.3067,0.1116,0
"St_Peter",0.0173,-0.1603,0.195,0
"St_Vincent",0.1291,-0.0771,0.3353,0
"Tower",0.0458,-0.1599,0.2515,0
"Warroad",0.0805,-0.086,0.2471,0
"Winnibigoshish",-0.0878,-0.1817,0.0061,0
"Winona",0.1594,0.0249,0.2939,1
"Coastal",1.0788,-0.9849,3.1426,0
"Inland",2.2908,-1.7581,6.3396,0
"All",3.3696,-2.3576,9.0969,0

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY", 0.1033, -0.1358, 0.3423, 0
"Boston MA", 0.0349, -0.0942, 0.1641, 0
"Portland ME", 0.1415, -0.1022, 0.3853, 0
"Gardiner ME", 0.2825, 0.0656, 0.4994, 1
"Albany NY", 0.1891, 0.0254, 0.3528, 1
"Concord NH", 0.2102, -0.0465, 0.4669, 0
"Montreal Q", 0.1739, 0.0566, 0.2913, 1
"Lakeport NH", 0.2488, 0.0605, 0.437, 1
"Burlington VT", 0.1075, -0.0651, 0.28, 0
"Cornwall VT", 0.1211, -0.0509, 0.293, 0
"Northfield VT", 0.0893, -0.1133, 0.2919, 0
"Corinth VT", 0.2419, 0.0575, 0.4264, 1
"Hanover NH", 0.0885, -0.1187, 0.2957, 0
"Rochester NY", 0.0485, -0.0567, 0.1537, 0
"Buffalo NY", 0.0272, -0.0964, 0.1509, 0
"Middletown CT", -0.1232, -0.4458, 0.1995, 0
"Ithaca NY", 0.1151, 0.0179, 0.2122, 1
"Amherst MA", 0.1458, 0.0275, 0.2641, 1
"Setauket Strong NY", 0.2685, 0.0949, 0.4421, 1
"Fitchburg MA", -0.1928, -0.3635, -0.022, 1
"Providence RI", 0.1644, -0.0265, 0.3553, 0
"Waterville ME", 0.1838, -0.032, 0.3997, 0
"Lowville NY", 0.0885, -0.0695, 0.2465, 0
"Cooperstown NY", 0.4266, 0.2474, 0.6058, 1
"Berlin NH", 0.1704, 0.0084, 0.3325, 1
"Farmington ME", 0.2075, -0.0915, 0.5065, 0
"Eastport ME", 0.3047, -0.0475, 0.657, 0
"Coastal", 1.3422, -0.3342, 3.0187, 0
"Inland", 2.5254, 0.3422, 4.7086, 1
"All", 3.8677, 0.0388, 7.6965, 1

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Blaine"	0.0566	-0.1259	0.2391	0
"Bellingham"	-0.0597	-0.1905	0.0711	0
"Quil"	0.1062	-0.2288	0.4412	0
"Clearwater"	-0.0359	-0.5303	0.4585	0
"Aberdeen"	-0.0259	-0.3916	0.3399	0
"Raymond"	-0.0287	-0.3943	0.3369	0
"Astoria"	0.2014	-0.1919	0.5947	0
"Tillamook"	-0.0249	-0.4613	0.4116	0
"Newport"	-0.3608	-1.0918	0.3702	0
"Florence"	-0.0161	-0.4068	0.3746	0
"North Bend"	-0.1994	-0.5749	0.1762	0
"Bandon"	-0.0601	-0.376	0.2558	0
"Port"	-0.1693	-0.5588	0.2202	0
"Crescent City"	0.0523	-0.4019	0.5066	0
"Eureka"	-0.0058	-0.3364	0.3249	0
"Upper Mattole"	-0.0432	-0.6074	0.5209	0
"Fort Bragg"	0.0045	-0.3674	0.3765	0
"Ukiah"	-0.224	-0.5994	0.1513	0
"Healdsburg"	-0.1947	-0.5731	0.1837	0
"San Francisco"	-0.0732	-0.3077	0.1612	0
"Santa Cruz"	-0.043	-0.3538	0.2678	0
"Big Sur"	-0.0869	-0.5213	0.3475	0
"Paso Robles"	0.034	-0.1381	0.2061	0
"Santa Maria"	-0.0415	-0.2233	0.1404	0
"Santa Barbara"	-0.0077	-0.3235	0.3082	0
"Los Angeles"	-0.0051	-0.2095	0.1994	0
"Santa Ana"	-0.0698	-0.2494	0.1097	0
"Escondido"	-0.0308	-0.2365	0.1749	0
"San Diego"	-0.0414	-0.1536	0.0708	0
"Coastal"	-0.715	-4.2105	2.7806	0
"Inland"	-0.6776	-4.3017	2.9464	0
"All"	-1.3926	-8.4318	5.6466	0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	0.0637	-0.1422	0.2697	0
"Galveston"	0.1571	-0.1616	0.4759	0
"Shreveport"	0.051	-0.3851	0.487	0
"Vicksburg"	-0.1119	-0.4717	0.2479	0
"New Orleans"	0.0126	-0.3744	0.3996	0
"Memphis"	0.0893	-0.1535	0.3321	0
"Mobile"	-0.0126	-0.22	0.1949	0
"Nashville"	0.2653	0.0665	0.4641	1
"Montgomery"	-0.126	-0.6282	0.3762	0
"Atlanta"	0.095	-0.2201	0.4101	0
"Knoxville"	0.2905	0.0975	0.4835	1
"Macon"	0.126	-0.0499	0.3019	0
"Quitman"	-0.0024	-0.3638	0.3589	0
"Augusta"	0.1343	-0.2406	0.5092	0
"Key West"	-0.0302	-0.145	0.0845	0
"Jacksonville"	0.1156	-0.1934	0.4245	0
"Lenoir"	0.2294	-0.0094	0.4682	0
"Savannah"	-0.0279	-0.3148	0.259	0
"Charleston"	0.1365	-0.1064	0.3793	0
"Lynchburg"	0.1506	-0.0528	0.3539	0
"Wilmington"	0.1989	-0.1338	0.5315	0
"Weldon"	0.3151	0.0965	0.5337	1
"Washington"	0.2111	0.0941	0.3282	1
"Norfolk"	0.2162	0.0533	0.3792	1
"Coastal"	0.7661	-0.7299	2.2622	0
"Inland"	1.781	-1.0264	4.5885	0
"All"	2.5472	-1.673	6.7674	0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	-0.0112	-0.1021	0.0796	0
"Galveston"	-0.0337	-0.1939	0.1265	0
"Shreveport"	0.0981	-0.0893	0.2855	0
"Vicksburg"	0.0416	-0.1363	0.2195	0
"New Orleans"	0.0857	-0.0295	0.2009	0
"Memphis"	0.1012	-0.0982	0.3005	0
"Mobile"	0.0844	0.0081	0.1607	1
"Nashville"	0.0303	-0.1217	0.1823	0
"Montgomery"	0.0086	-0.0761	0.0933	0
"Atlanta"	0.0376	-0.0503	0.1256	0
"Knoxville"	0.0224	-0.1385	0.1832	0
"Macon"	-0.0342	-0.1556	0.0872	0
"Quitman"	-0.0727	-0.1241	-0.0213	1
"Augusta"	-0.0215	-0.1438	0.1009	0
"Key West"	0.0321	-0.0112	0.0754	0
"Jacksonville"	0.0278	-0.0911	0.1467	0
"Lenoir"	-0.0045	-0.091	0.082	0
"Savannah"	-0.0027	-0.1071	0.1016	0
"Charleston"	0.0655	-0.1858	0.3168	0
"Lynchburg"	0.0162	-0.1155	0.148	0
"Wilmington"	0.1658	-0.0502	0.3818	0
"Weldon"	0.0806	-0.0751	0.2362	0
"Washington"	-0.0359	-0.1442	0.0724	0
"Norfolk"	0.0168	-0.1892	0.2229	0
"Coastal"	0.4416	-0.5971	1.4804	0
"Inland"	0.2566	-1.3759	1.8891	0
"All"	0.6982	-1.8812	3.2777	0

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY", 0.1381, -0.0289, 0.3051, 0
"Boston MA", 0.0939, 0.0284, 0.1595, 1
"Portland ME", 0.1211, 0.0073, 0.2348, 1
"Gardiner ME", 0.1252, 0.0231, 0.2274, 1
"Albany NY", 0.1295, 0.036, 0.2229, 1
"Concord NH", 0.089, -0.0649, 0.2429, 0
"Montreal Q", -0.0196, -0.1573, 0.1181, 0
"Lakeport NH", 0.0803, -0.1141, 0.2747, 0
"Burlington VT", 0.1131, 0.0323, 0.1939, 1
"Cornwall VT", 0.1296, 0.0542, 0.205, 1
"Northfield VT", 0.2522, 0.1515, 0.3528, 1
"Corinth VT", 0.1418, 0.0223, 0.2614, 1
"Hanover NH", 0.0943, 0.0238, 0.1648, 1
"Rochester NY", 0.0387, -0.0577, 0.135, 0
"Buffalo NY", 0.1241, -0.0056, 0.2537, 0
"Middletown CT", 0.0361, -0.1112, 0.1834, 0
"Ithaca NY", 0.0707, -0.0154, 0.1567, 0
"Amherst MA", 0.0699, -0.0688, 0.2086, 0
"Setauket Strong NY", 0.0949, -0.06, 0.2498, 0
"Fitchburg MA", 0.078, -0.0384, 0.1944, 0
"Providence RI", 0.1103, -0.0944, 0.315, 0
"Waterville ME", 0.1432, 0.091, 0.1954, 1
"Lowville NY", 0.0625, -0.0484, 0.1735, 0
"Cooperstown NY", 0.0656, -0.1882, 0.3195, 0
"Berlin NH", 0.1005, -0.0143, 0.2154, 0
"Farmington ME", 0.1438, 0.061, 0.2265, 1
"Eastport ME", 0.261, 0.1077, 0.4142, 1
"Coastal", 1.535, 0.4127, 2.6572, 1
"Inland", 1.3527, -0.1775, 2.883, 0
"All", 2.8877, 0.306, 5.4694, 1

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.1429, 0.0388, 0.247, 1
 "Milwaukee WI", 0.1302, 0.0332, 0.2271, 1
 "Green Bay WI", 0.059, -0.0788, 0.1968, 0
 "Chippewa Falls WI", 0.0355, -0.0622, 0.1331, 0
 "Medford WI", 0.0255, -0.0583, 0.1093, 0
 "Dubuque IA", 0.1466, 0.0162, 0.277, 1
 "Des Moines IA", 0.1096, 0.0217, 0.1975, 1
 "Cedar Rapids IA", 0.1642, 0.1019, 0.2264, 1
 "Davenport IA", 0.1359, 0.0704, 0.2013, 1
 "Sioux City IA", 0.0606, -0.0106, 0.1318, 0
 "Aurora IL", 0.1198, 0.0439, 0.1957, 1
 "Denison IA", 0.0995, 0.0216, 0.1774, 1
 "Spencer IA", 0.0676, -0.0224, 0.1576, 0
 "Fort Dodge IA", 0.0986, 0.0207, 0.1765, 1
 "Rockford IL", 0.0667, 0.0086, 0.1247, 1
 "Sioux Falls SD", 0.0164, -0.0714, 0.1042, 0
 "Charles City IA", 0.1116, 0.0298, 0.1933, 1
 "Hillsboro WI", 0.1027, -0.0328, 0.2382, 0
 "Stevens Point WI", 0.0577, -0.0346, 0.1501, 0
 "Iron Mountain MI", 0.0446, 0.0043, 0.0849, 1
 "Park Falls WI", 0.0313, -0.0314, 0.094, 0
 "Ashland WI", 0.0083, -0.1036, 0.1202, 0
 "Hancock-Houghton AP MI", -0.1193, -0.293, 0.0544, 0
 "Oshkosh WI", 0.1061, 0.0085, 0.2036, 1
 "Shawano WI", 0.0742, 0.0233, 0.125, 1
 "Spooner WI", 0.0603, -0.0114, 0.1321, 0
 "Grundy Center IA", 0.0538, -0.0383, 0.1459, 0
 "Lansing IA", 0.1147, -0.0212, 0.2505, 0
 "Rhineland WI", 0.0627, -0.0161, 0.1415, 0
 "Bergland Dam MI", 0.2261, 0.0995, 0.3527, 1
 "Alexandria", 0.039, -0.0385, 0.1164, 0
 "Beardsley", 0.0361, -0.0741, 0.1462, 0
 "Canby", 0.0685, 0.0096, 0.1273, 1
 "Crookston", -0.0171, -0.086, 0.0517, 0
 "Duluth", 0.0893, 0.0317, 0.1469, 1
 "Fairmont", 0.0567, -0.016, 0.1293, 0
 "Farmington", 0.1321, 0.0208, 0.2434, 1
 "Fergus_Falls", 0.0339, -0.0581, 0.126, 0
 "Grand_Meadow", 0.0817, -0.0765, 0.2398, 0
 "Grand_Portage", 0.0725, -0.0286, 0.1737, 0
 "Hinckley", 0.1062, 0.0119, 0.2006, 1
 "International_Falls", -0.0137, -0.08, 0.0527, 0
 "Leech_Lake", 0.0075, -0.073, 0.0881, 0
 "Little_Falls", 0.0742, 0.0012, 0.1472, 1
 "Montevideo", 0.0947, 0.0389, 0.1504, 1
 "Moorhead", 0.0412, -0.1458, 0.2283, 0
 "Morris", 0.0532, -0.0145, 0.1209, 0
 "Park_Rapids", -0.0362, -0.1286, 0.0563, 0

"Pine_River_Dam",0.0366,-0.062,0.1351,0
"Pipestone",0.0834,0.0347,0.132,1
"Pokegama_Dam",0.0474,-0.0676,0.1624,0
"Red_Lake_Indian_Agency",-0.0437,-0.1114,0.0239,0
"Redwodd_Falls",0.0829,-0.0325,0.1983,0
"St_Cloud",0.041,-0.0621,0.1442,0
"St_Paul",0.0583,-0.0501,0.1667,0
"St_Peter",0.0905,0.0277,0.1534,1
"St_Vincent",0.0575,-0.0327,0.1478,0
"Tower",0.0438,-0.0278,0.1155,0
"Warroad",0.0801,-0.0324,0.1927,0
"Winnibigoshish",0.0336,-0.0593,0.1265,0
"Winona",0.0731,-0.0749,0.221,0
"Coastal",1.6043,-0.3498,3.5584,0
"Inland",2.4129,1.1232,3.7026,1
"All",4.0172,0.9994,7.0351,1

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Blaine"	0.0021	-0.0935	0.0976	0
"Bellingham"	0.0577	-0.0071	0.1226	0
"Quil"	-0.0064	-0.2399	0.2271	0
"Clearwater"	-0.1174	-0.4227	0.1878	0
"Aberdeen"	0.005	-0.1221	0.1321	0
"Raymond"	-0.0372	-0.1952	0.1209	0
"Astoria"	-0.2054	-0.3832	-0.0276	1
"Tillamook"	-0.085	-0.2957	0.1257	0
"Newport"	-0.1769	-0.5208	0.167	0
"Florence"	0.0249	-0.131	0.1807	0
"North Bend"	0.0103	-0.1659	0.1866	0
"Bandon"	0.0929	-0.0999	0.2858	0
"Port"	-0.0201	-0.2496	0.2095	0
"Crescent City"	-0.1207	-0.268	0.0267	0
"Eureka"	-0.0165	-0.189	0.1559	0
"Upper Mattole"	-0.0411	-0.2609	0.1786	0
"Fort Bragg"	0.0849	-0.0293	0.1991	0
"Ukiah"	-0.0049	-0.157	0.1472	0
"Healdsburg"	0.0294	-0.1251	0.1839	0
"San Francisco"	0.0414	-0.0145	0.0973	0
"Santa Cruz"	0.0514	-0.0452	0.1479	0
"Big Sur"	0.0799	-0.0252	0.185	0
"Paso Robles"	-0.0091	-0.0655	0.0473	0
"Santa Maria"	0.008	-0.0409	0.0569	0
"Santa Barbara"	0.0079	-0.0701	0.0859	0
"Los Angeles"	0.0116	-0.0507	0.0738	0
"Santa Ana"	-0.0145	-0.091	0.062	0
"Escondido"	-0.0382	-0.1109	0.0346	0
"San Diego"	0.0027	-0.045	0.0503	0
"Coastal"	-0.2553	-1.4848	0.9742	0
"Inland"	-0.1281	-1.3111	1.0549	0
"All"	-0.3834	-2.7546	1.9877	0

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.2719, 0.1411, 0.4027, 1
 "Milwaukee WI", 0.1805, -0.003, 0.364, 0
 "Green Bay WI", 0.2036, 0.0703, 0.337, 1
 "Chippewa Falls WI", 0.1676, 0.0238, 0.3114, 1
 "Medford WI", 0.1278, -0.016, 0.2716, 0
 "Dubuque IA", -0.0097, -0.3052, 0.2858, 0
 "Des Moines IA", 0.2139, 0.0124, 0.4154, 1
 "Cedar Rapids IA", 0.0894, -0.0322, 0.211, 0
 "Davenport IA", 0.192, 0.0601, 0.3239, 1
 "Sioux City IA", 0.1393, 0.0253, 0.2534, 1
 "Aurora IL", 0.192, 0.0526, 0.3314, 1
 "Denison IA", 0.1174, -0.0482, 0.2831, 0
 "Spencer IA", 0.1761, 0.006, 0.3462, 1
 "Fort Dodge IA", 0.1286, -0.0165, 0.2738, 0
 "Rockford IL", 0.0388, -0.1225, 0.2, 0
 "Sioux Falls SD", 0.1289, 0.0181, 0.2398, 1
 "Charles City IA", 0.2111, 0.0695, 0.3527, 1
 "Hillsboro WI", 0.2947, 0.1588, 0.4305, 1
 "Stevens Point WI", 0.1754, 0.0506, 0.3003, 1
 "Iron Mountain MI", 0.0244, -0.1235, 0.1724, 0
 "Park Falls WI", 0.0512, -0.1508, 0.2532, 0
 "Ashland WI", -0.1765, -0.3063, -0.0467, 1
 "Hancock-Houghton AP MI", -0.3017, -0.6267, 0.0232, 0
 "Oshkosh WI", 0.2369, 0.0778, 0.396, 1
 "Shawano WI", 0.1153, -0.0427, 0.2732, 0
 "Spooner WI", 0.0327, -0.1123, 0.1776, 0
 "Grundy Center IA", 0.1713, 0.0378, 0.3048, 1
 "Lansing IA", 0.2882, 0.1055, 0.4708, 1
 "Rhineland WI", 0.1597, 0.0221, 0.2974, 1
 "Bergland Dam MI", 0.0909, -0.1281, 0.31, 0
 "Alexandria", 0.0112, -0.1146, 0.1369, 0
 "Beardsley", 0.1416, -0.0048, 0.288, 0
 "Canby", 0.1027, 0.0041, 0.2013, 1
 "Crookston", 0.0044, -0.1187, 0.1276, 0
 "Duluth", -0.0162, -0.111, 0.0785, 0
 "Fairmont", 0.081, -0.1068, 0.2688, 0
 "Farmington", 0.1946, 0.0357, 0.3534, 1
 "Fergus_Falls", 0.1245, -0.065, 0.3139, 0
 "Grand_Meadow", 0.2523, 0.1271, 0.3774, 1
 "Grand_Portage", 0.1875, 0.047, 0.328, 1
 "Hinckley", 0.1447, 0.0141, 0.2754, 1
 "International_Falls", 0.0687, -0.0514, 0.1887, 0
 "Leech_Lake", 0.0445, -0.0471, 0.1362, 0
 "Little_Falls", 0.1105, -0.0622, 0.2831, 0
 "Montevideo", 0.0309, -0.1392, 0.201, 0
 "Moorhead", 0.2004, -0.0234, 0.4243, 0
 "Morris", 0.0988, 0.0222, 0.1754, 1
 "Park_Rapids", -0.146, -0.2662, -0.0257, 1

"Pine_River_Dam",0.0476,-0.0361,0.1312,0
"Pipestone",0.1233,0.028,0.2185,1
"Pokegama_Dam",0.0186,-0.0835,0.1207,0
"Red_Lake_Indian_Agency",-0.0464,-0.2243,0.1315,0
"Redwodd_Falls",0.1818,0.0534,0.3102,1
"St_Cloud",0.0653,-0.1285,0.2592,0
"St_Paul",0.0476,-0.2128,0.308,0
"St_Peter",0.1429,0.0126,0.2732,1
"St_Vincent",0.1703,0.0356,0.305,1
"Tower",0.0296,-0.1691,0.2283,0
"Warroad",0.2261,0.0963,0.3559,1
"Winnibigoshish",0.0144,-0.1369,0.1657,0
"Winona",0.2625,0.1706,0.3543,1
"Coastal",2.9195,1.4783,4.3608,1
"Inland",3.7319,1.1544,6.3093,1
"All",6.6514,3.114,10.1888,1

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY", 0.3636, 0.0291, 0.6981, 1
"Boston MA", -0.0581, -0.339, 0.2229, 0
"Portland ME", 0.2342, 0.0474, 0.4209, 1
"Gardiner ME", 0.1988, -0.1317, 0.5293, 0
"Albany NY", 0.233, 0.0462, 0.4197, 1
"Concord NH", 0.2601, -0.0089, 0.5291, 0
"Montreal Q", 0.1869, 0.0219, 0.352, 1
"Lakeport NH", 0.3975, 0.1574, 0.6375, 1
"Burlington VT", 0.1948, 0.0699, 0.3198, 1
"Cornwall VT", 0.2469, 0.1103, 0.3835, 1
"Northfield VT", 0.2948, 0.1099, 0.4797, 1
"Corinth VT", 0.3006, 0.0797, 0.5215, 1
"Hanover NH", 0.169, 0.0161, 0.3218, 1
"Rochester NY", 0.156, 0.0369, 0.2752, 1
"Buffalo NY", 0.1606, 0.0027, 0.3186, 1
"Middletown CT", -0.0969, -0.4353, 0.2416, 0
"Ithaca NY", 0.1549, 0.0553, 0.2545, 1
"Amherst MA", 0.2319, 0.0721, 0.3917, 1
"Setauket Strong NY", 0.2883, 0.071, 0.5056, 1
"Fitchburg MA", -0.0819, -0.3582, 0.1944, 0
"Providence RI", 0.1817, -0.0021, 0.3656, 0
"Waterville ME", 0.142, -0.0589, 0.3428, 0
"Lowville NY", 0.1158, -0.02, 0.2515, 0
"Cooperstown NY", 0.4664, 0.1976, 0.7351, 1
"Berlin NH", 0.2464, 0.1017, 0.391, 1
"Farmington ME", 0.1905, -0.0538, 0.4347, 0
"Eastport ME", 0.295, -0.053, 0.6429, 0
"Coastal", 2.3098, 0.5832, 4.0364, 1
"Inland", 3.1631, 0.8981, 5.428, 1
"All", 5.4729, 1.659, 9.2867, 1

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Blaine"	0.0844	-0.0466	0.2154	0
"Bellingham"	-0.0267	-0.1233	0.0699	0
"Quil"	-0.0066	-0.3579	0.3447	0
"Clearwater"	-0.4407	-0.985	0.1036	0
"Aberdeen"	0.0213	-0.2192	0.2619	0
"Raymond"	-0.2008	-0.6417	0.2401	0
"Astoria"	-0.0823	-0.6182	0.4535	0
"Tillamook"	-0.1395	-0.4299	0.1509	0
"Newport"	-0.7088	-1.1704	-0.2472	1
"Florence"	-0.0727	-0.3405	0.1951	0
"North Bend"	0.096	-0.2764	0.4684	0
"Bandon"	-0.1502	-0.3716	0.0711	0
"Port"	-0.2287	-0.5002	0.0429	0
"Crescent City"	-0.0067	-0.3641	0.3508	0
"Eureka"	-0.0296	-0.2909	0.2316	0
"Upper Mattole"	-0.1667	-0.6606	0.3272	0
"Fort Bragg"	0.0653	-0.1849	0.3155	0
"Ukiah"	-0.1602	-0.4552	0.1348	0
"Healdsburg"	-0.1274	-0.3927	0.1378	0
"San Francisco"	0.0563	-0.1435	0.2562	0
"Santa Cruz"	0.0036	-0.1966	0.2037	0
"Big Sur"	0.0274	-0.2768	0.3316	0
"Paso Robles"	0.0475	-0.0585	0.1536	0
"Santa Maria"	0.024	-0.1346	0.1826	0
"Santa Barbara"	0.0325	-0.1632	0.2283	0
"Los Angeles"	0.0094	-0.1831	0.202	0
"Santa Ana"	-0.0176	-0.2102	0.175	0
"Escondido"	0.0055	-0.1999	0.2109	0
"San Diego"	0.026	-0.1215	0.1735	0
"Coastal"	-0.8243	-2.9273	1.2787	0
"Inland"	-1.2415	-3.4097	0.9267	0
"All"	-2.0658	-6.2747	2.1432	0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	0.1683	0.0002	0.3363	1
"Galveston"	0.286	0.0401	0.5318	1
"Shreveport"	0.285	-0.0484	0.6184	0
"Vicksburg"	0.1258	-0.3717	0.6233	0
"New Orleans"	0.1348	-0.1617	0.4313	0
"Memphis"	0.2082	-0.0058	0.4222	0
"Mobile"	0.087	-0.1321	0.306	0
"Nashville"	0.1192	-0.133	0.3714	0
"Montgomery"	0.1311	-0.2945	0.5566	0
"Atlanta"	0.1643	-0.0733	0.4019	0
"Knoxville"	0.2339	0.0056	0.4623	1
"Macon"	0.1271	-0.0254	0.2796	0
"Quitman"	-0.0012	-0.3201	0.3176	0
"Augusta"	0.1497	-0.1241	0.4234	0
"Key West"	0.0799	-0.0927	0.2526	0
"Jacksonville"	0.0775	-0.127	0.2821	0
"Lenoir"	0.1114	-0.1764	0.3993	0
"Savannah"	-0.1032	-0.2995	0.0932	0
"Charleston"	0.0898	-0.1788	0.3583	0
"Lynchburg"	0.1718	-0.0152	0.3589	0
"Wilmington"	0.2712	0.0738	0.4686	1
"Weldon"	0.2909	0.0535	0.5282	1
"Washington"	0.1392	-0.0649	0.3434	0
"Norfolk"	0.192	-0.001	0.3851	0
"Coastal"	1.1151	0.0899	2.1402	1
"Inland"	2.4247	0.3457	4.5038	1
"All"	3.5398	0.5427	6.5369	1

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.388, 0.1401, 0.6358, 1
 "Milwaukee WI", 0.0003, -0.4169, 0.4175, 0
 "Green Bay WI", 0.3257, -0.0021, 0.6534, 0
 "Chippewa Falls WI", 0.211, -0.0834, 0.5054, 0
 "Medford WI", 0.1605, -0.2759, 0.5968, 0
 "Dubuque IA", 0.2249, -0.1812, 0.631, 0
 "Des Moines IA", -0.0274, -0.4555, 0.4006, 0
 "Cedar Rapids IA", 0.0933, -0.224, 0.4106, 0
 "Davenport IA", 0.2299, -0.1508, 0.6106, 0
 "Sioux City IA", 0.169, -0.1567, 0.4948, 0
 "Aurora IL", 0.1639, -0.1909, 0.5187, 0
 "Denison IA", 0.0745, -0.3752, 0.5243, 0
 "Spencer IA", 0.2113, -0.3565, 0.7792, 0
 "Fort Dodge IA", 0.0092, -0.4002, 0.4185, 0
 "Rockford IL", 0.1332, -0.1356, 0.4021, 0
 "Sioux Falls SD", 0.1821, -0.0689, 0.4331, 0
 "Charles City IA", 0.2883, -0.1352, 0.7119, 0
 "Hillsboro WI", 0.3932, 0.0523, 0.734, 1
 "Stevens Point WI", 0.2506, -0.1111, 0.6122, 0
 "Iron Mountain MI", 0.172, -0.1038, 0.4478, 0
 "Park Falls WI", 0.23, -0.2293, 0.6893, 0
 "Ashland WI", -0.2282, -0.5876, 0.1312, 0
 "Hancock-Houghton AP MI", -0.4566, -1.4187, 0.5055, 0
 "Oshkosh WI", 0.2731, -0.2199, 0.7661, 0
 "Shawano WI", 0.2336, -0.1851, 0.6523, 0
 "Spooner WI", -0.0872, -0.3863, 0.212, 0
 "Grundy Center IA", 0.115, -0.2908, 0.5208, 0
 "Lansing IA", 0.3624, -0.0043, 0.7291, 0
 "Rhinelander WI", 0.2913, -0.0485, 0.6311, 0
 "Bergland Dam MI", 0.2096, -0.0946, 0.5138, 0
 "Alexandria", -0.0765, -0.4682, 0.3153, 0
 "Beardsley", 0.1528, -0.1666, 0.4721, 0
 "Canby", 0.0927, -0.1437, 0.3291, 0
 "Crookston", -0.0846, -0.4411, 0.2719, 0
 "Duluth", -0.0095, -0.1846, 0.1656, 0
 "Fairmont", -0.1231, -0.4846, 0.2384, 0
 "Farmington", 0.2694, -0.1346, 0.6733, 0
 "Fergus_Falls", 0.2813, 0.0032, 0.5595, 1
 "Grand_Meadow", 0.2122, -0.0405, 0.4649, 0
 "Grand_Portage", 0.3678, 0.1873, 0.5483, 1
 "Hinckley", 0.1143, -0.2833, 0.5118, 0
 "International_Falls", 0.2154, 0.0766, 0.3543, 1
 "Leech_Lake", 0.0012, -0.1851, 0.1874, 0
 "Little_Falls", 0.2649, -0.0531, 0.5829, 0
 "Montevideo", 0.0663, -0.2533, 0.3858, 0
 "Moorhead", 0.1512, -0.603, 0.9055, 0
 "Morris", 0.0192, -0.1732, 0.2116, 0
 "Park_Rapids", -0.3325, -0.5219, -0.143, 1

"Pine_River_Dam",-0.0221,-0.1873,0.1431,0
"Pipestone",0.0774,-0.2127,0.3674,0
"Pokegama_Dam",-0.0934,-0.3216,0.1347,0
"Red_Lake_Indian_Agency",-0.2108,-0.5744,0.1529,0
"Redwodd_Falls",0.1571,-0.2636,0.5779,0
"St_Cloud",0.1859,-0.2361,0.6079,0
"St_Paul",-0.1945,-0.6124,0.2233,0
"St_Peter",0.0349,-0.3204,0.3902,0
"St_Vincent",0.2585,-0.1538,0.6708,0
"Tower",0.0926,-0.318,0.5033,0
"Warroad",0.1615,-0.1719,0.4949,0
"Winnibigoshish",-0.175,-0.3632,0.0131,0
"Winona",0.3192,0.0501,0.5883,1
"Coastal",2.1739,-1.9333,6.2811,0
"Inland",4.5964,-3.4843,12.6772,0
"All",6.7703,-4.6416,18.1822,0

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY", 0.2069, -0.271, 0.6848, 0
"Boston MA", 0.0738, -0.1827, 0.3303, 0
"Portland ME", 0.2842, -0.1992, 0.7677, 0
"Gardiner ME", 0.5657, 0.1324, 0.999, 1
"Albany NY", 0.3799, 0.0546, 0.7051, 1
"Concord NH", 0.4215, -0.0901, 0.933, 0
"Montreal Q", 0.3492, 0.1156, 0.5827, 1
"Lakeport NH", 0.4993, 0.1266, 0.872, 1
"Burlington VT", 0.216, -0.1274, 0.5594, 0
"Cornwall VT", 0.2432, -0.0989, 0.5853, 0
"Northfield VT", 0.18, -0.2247, 0.5847, 0
"Corinth VT", 0.4852, 0.1183, 0.8522, 1
"Hanover NH", 0.1787, -0.2332, 0.5905, 0
"Rochester NY", 0.0978, -0.1114, 0.3071, 0
"Buffalo NY", 0.0554, -0.1925, 0.3034, 0
"Middletown CT", -0.2456, -0.8922, 0.401, 0
"Ithaca NY", 0.2307, 0.0363, 0.4251, 1
"Amherst MA", 0.2931, 0.0555, 0.5307, 1
"Setauket Strong NY", 0.5378, 0.1893, 0.8864, 1
"Fitchburg MA", -0.3842, -0.727, -0.0415, 1
"Providence RI", 0.3324, -0.0501, 0.715, 0
"Waterville ME", 0.3686, -0.0626, 0.7998, 0
"Lowville NY", 0.1788, -0.1368, 0.4944, 0
"Cooperstown NY", 0.8535, 0.4964, 1.2106, 1
"Berlin NH", 0.3416, 0.0183, 0.6649, 1
"Farmington ME", 0.4162, -0.1779, 1.0103, 0
"Eastport ME", 0.6104, -0.0916, 1.3123, 0
"Coastal", 2.6988, -0.6392, 6.0369, 0
"Inland", 5.0714, 0.7316, 9.4113, 1
"All", 7.7703, 0.1543, 15.3863, 1

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Blaine"	0.1137	-0.251	0.4784	0
"Bellingham"	-0.1189	-0.3804	0.1425	0
"Quil"	0.2133	-0.456	0.8826	0
"Clearwater"	-0.0699	-1.0583	0.9186	0
"Aberdeen"	-0.0505	-0.7808	0.6798	0
"Raymond"	-0.0566	-0.7869	0.6737	0
"Astoria"	0.4036	-0.3824	1.1895	0
"Tillamook"	-0.0483	-0.9201	0.8235	0
"Newport"	-0.7208	-2.1833	0.7417	0
"Florence"	-0.0313	-0.8123	0.7496	0
"North Bend"	-0.3985	-1.1496	0.3526	0
"Bandon"	-0.1195	-0.7512	0.5121	0
"Port"	-0.3377	-1.1155	0.4401	0
"Crescent City"	0.1049	-0.8034	1.0131	0
"Eureka"	-0.0113	-0.6721	0.6495	0
"Upper Mattole"	-0.0861	-1.2136	1.0415	0
"Fort Bragg"	0.0092	-0.7347	0.753	0
"Ukiah"	-0.448	-1.1986	0.3026	0
"Healdsburg"	-0.3893	-1.1459	0.3673	0
"San Francisco"	-0.1464	-0.615	0.3222	0
"Santa Cruz"	-0.0857	-0.7064	0.5349	0
"Big Sur"	-0.1734	-1.0406	0.6938	0
"Paso Robles"	0.068	-0.2761	0.4121	0
"Santa Maria"	-0.0828	-0.4462	0.2807	0
"Santa Barbara"	-0.0154	-0.6471	0.6163	0
"Los Angeles"	-0.0099	-0.4185	0.3988	0
"Santa Ana"	-0.1396	-0.4987	0.2195	0
"Escondido"	-0.0616	-0.473	0.3499	0
"San Diego"	-0.0828	-0.3073	0.1416	0
"Coastal"	-1.4239	-8.41	5.5622	0
"Inland"	-1.3478	-8.5863	5.8908	0
"All"	-2.7717	-16.8359	11.2925	0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	0.1277	-0.2846	0.5399	0
"Galveston"	0.3148	-0.3234	0.9529	0
"Shreveport"	0.1023	-0.7709	0.9755	0
"Vicksburg"	-0.2231	-0.9444	0.4981	0
"New Orleans"	0.0259	-0.7488	0.8006	0
"Memphis"	0.1791	-0.3068	0.665	0
"Mobile"	-0.0242	-0.4395	0.3911	0
"Nashville"	0.531	0.1326	0.9293	1
"Montgomery"	-0.2512	-1.2565	0.754	0
"Atlanta"	0.1908	-0.4397	0.8213	0
"Knoxville"	0.581	0.1941	0.9679	1
"Macon"	0.2525	-0.0996	0.6047	0
"Quitman"	-0.0041	-0.7244	0.7162	0
"Augusta"	0.2691	-0.4811	1.0194	0
"Key West"	-0.0585	-0.2888	0.1717	0
"Jacksonville"	0.2325	-0.3862	0.8511	0
"Lenoir"	0.4594	-0.0188	0.9375	0
"Savannah"	-0.055	-0.6291	0.5192	0
"Charleston"	0.2741	-0.2126	0.7608	0
"Lynchburg"	0.3013	-0.1057	0.7084	0
"Wilmington"	0.3989	-0.2677	1.0655	0
"Weldon"	0.6308	0.1947	1.0668	1
"Washington"	0.4231	0.1907	0.6555	1
"Norfolk"	0.434	0.1084	0.7596	1
"Coastal"	1.5425	-1.4582	4.5432	0
"Inland"	3.5696	-2.055	9.1942	0
"All"	5.1121	-3.3462	13.5705	0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	-0.0014	-0.0033	0.0004	0
"Galveston"	0.0001	-0.0002	0.0005	0
"Shreveport"	0.0006	0	0.0012	0
"Vicksburg"	0.0005	-0.0003	0.0014	0
"New Orleans"	0.0006	0.0002	0.0011	1
"Memphis"	0.0006	0.0002	0.0009	1
"Mobile"	0.0005	0.0001	0.0008	1
"Nashville"	0.0003	0.0001	0.0005	1
"Montgomery"	0.0003	-0.0001	0.0007	0
"Atlanta"	0.0002	-0.0004	0.0008	0
"Knoxville"	0.0003	-0.0001	0.0006	0
"Macon"	-0.0016	-0.0043	0.0011	0
"Quitman"	-0.0024	-0.0034	-0.0015	1
"Augusta"	0.0001	-0.0002	0.0004	0
"Key West"	0.0004	0.0003	0.0005	1
"Jacksonville"	0.0005	0	0.001	0
"Lenoir"	-0.0023	-0.004	-0.0005	1
"Savannah"	0.0003	0	0.0007	0
"Charleston"	0.0004	-0.0005	0.0013	0
"Lynchburg"	0.0002	-0.0002	0.0007	0
"Wilmington"	0.0008	0.0002	0.0014	1
"Weldon"	-0.0001	-0.0018	0.0015	0
"Washington"	0.0002	0	0.0003	0
"Norfolk"	0.0004	-0.0001	0.0009	0
"Coastal"	0.0012	-0.0001	0.0025	0
"Inland"	-0.0003	-0.0033	0.0027	0
"All"	0.001	-0.0028	0.0047	0

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY", 0.0004, -0.0001, 0.001, 0
"Boston MA", 0.0002, 0, 0.0004, 0
"Portland ME", 0.0006, 0.0002, 0.001, 1
"Gardiner ME", 0.0003, -0.0011, 0.0017, 0
"Albany NY", 0.0004, 0.0001, 0.0007, 1
"Concord NH", 0, -0.0005, 0.0006, 0
"Montreal Q", -0.0001, -0.0005, 0.0003, 0
"Lakeport NH", -0.0007, -0.0019, 0.0005, 0
"Burlington VT", 0.0001, -0.0003, 0.0005, 0
"Cornwall VT", -0.0005, -0.001, 0, 0
"Northfield VT", 0.001, 0.0006, 0.0014, 1
"Corinth VT", -0.0002, -0.0008, 0.0004, 0
"Hanover NH", 0.0001, -0.0005, 0.0007, 0
"Rochester NY", 0.0001, 0, 0.0002, 0
"Buffalo NY", 0.0003, 0, 0.0007, 0
"Middletown CT", -0.0004, -0.001, 0.0001, 0
"Ithaca NY", 0.0001, -0.0002, 0.0003, 0
"Amherst MA", -0.0001, -0.0007, 0.0006, 0
"Setauket Strong NY", 0.0002, -0.0002, 0.0007, 0
"Fitchburg MA", -0.0004, -0.0009, 0.0001, 0
"Providence RI", 0, -0.0012, 0.0012, 0
"Waterville ME", -0.0008, -0.0013, -0.0002, 1
"Lowville NY", -0.0003, -0.001, 0.0004, 0
"Cooperstown NY", -0.0001, -0.0012, 0.0011, 0
"Berlin NH", 0.0003, -0.0013, 0.0019, 0
"Farmington ME", -0.0001, -0.0009, 0.0006, 0
"Eastport ME", 0.0012, 0.0005, 0.0018, 1
"Coastal", 0.0013, -0.0004, 0.003, 0
"Inland", 0.0013, -0.002, 0.0045, 0
"All", 0.003, -0.0012, 0.0072, 0

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.0003, 0, 0.0007, 0
 "Milwaukee WI", 0.0003, 0, 0.0007, 0
 "Green Bay WI", 0.0001, -0.0003, 0.0005, 0
 "Chippewa Falls WI", -0.0008, -0.0018, 0.0002, 0
 "Medford WI", -0.0017, -0.0036, 0.0001, 0
 "Dubuque IA", 0.0005, -0.0002, 0.0011, 0
 "Des Moines IA", 0.0003, 0, 0.0005, 0
 "Cedar Rapids IA", -0.0002, -0.0008, 0.0003, 0
 "Davenport IA", 0.0004, -0.0001, 0.0008, 0
 "Sioux City IA", 0.0002, -0.0002, 0.0005, 0
 "Aurora IL", -0.0004, -0.0011, 0.0003, 0
 "Denison IA", -0.0005, -0.0009, 0, 0
 "Spencer IA", -0.0006, -0.002, 0.0007, 0
 "Fort Dodge IA", -0.0001, -0.0012, 0.001, 0
 "Rockford IL", -0.0004, -0.0011, 0.0002, 0
 "Sioux Falls SD", -0.0013, -0.0026, 0.0001, 0
 "Charles City IA", 0.0003, -0.0005, 0.0011, 0
 "Hillsboro WI", -0.0012, -0.0018, -0.0006, 1
 "Stevens Point WI", -0.0017, -0.0031, -0.0003, 1
 "Iron Mountain MI", -0.0007, -0.0017, 0.0003, 0
 "Park Falls WI", -0.0009, -0.0017, -0.0001, 1
 "Ashland WI", -0.0009, -0.0013, -0.0005, 1
 "Hancock-Houghton AP MI", -0.0005, -0.0007, -0.0003, 1
 "Oshkosh WI", -0.0007, -0.002, 0.0007, 0
 "Shawano WI", -0.0007, -0.001, -0.0004, 1
 "Spooner WI", -0.0012, -0.0028, 0.0003, 0
 "Grundy Center IA", -0.0005, -0.0012, 0.0002, 0
 "Lansing IA", 0.0002, -0.0006, 0.001, 0
 "Rhineland WI", -0.0006, -0.0014, 0.0001, 0
 "Bergland Dam MI", -0.001, -0.0019, -0.0001, 1
 "Alexandria", -0.0007, -0.0015, 0.0002, 0
 "Beardsley", -0.0001, -0.0013, 0.0011, 0
 "Canby", -0.0011, -0.0018, -0.0004, 1
 "Crookston", -0.0005, -0.0018, 0.0008, 0
 "Duluth", 0.0001, 0, 0.0003, 0
 "Fairmont", -0.0008, -0.0023, 0.0008, 0
 "Farmington", 0, -0.0006, 0.0006, 0
 "Fergus_Falls", 0.0011, 0.0003, 0.0019, 1
 "Grand_Meadow", 0.0001, -0.0007, 0.001, 0
 "Grand_Portage", -0.0002, -0.0011, 0.0007, 0
 "Hinckley", -0.0008, -0.0023, 0.0008, 0
 "International_Falls", -0.0012, -0.0022, -0.0002, 1
 "Leech_Lake", -0.0004, -0.0017, 0.001, 0
 "Little_Falls", -0.0008, -0.0011, -0.0004, 1
 "Montevideo", 0.0003, -0.0001, 0.0007, 0
 "Moorhead", 0.0002, -0.0004, 0.0007, 0
 "Morris", -0.0007, -0.0015, 0.0001, 0
 "Park_Rapids", -0.0001, -0.0007, 0.0006, 0

"Pine_River_Dam",-0.001,-0.002,-0.0001,1
"Pipestone",-0.0003,-0.0013,0.0007,0
"Pokegama_Dam",-0.0003,-0.0014,0.0008,0
"Red_Lake_Indian_Agency",-0.0012,-0.0029,0.0005,0
"Redwodd_Falls",-0.0003,-0.0012,0.0006,0
"St_Cloud",-0.0012,-0.0032,0.0007,0
"St_Paul",0.0003,-0.0002,0.0008,0
"St_Peter",-0.0001,-0.0011,0.001,0
"St_Vincent",-0.0004,-0.0013,0.0004,0
"Tower",-0.0005,-0.0015,0.0005,0
"Warroad",-0.0002,-0.001,0.0005,0
"Winnibigoshish",-0.0003,-0.0015,0.0009,0
"Winona",-0.0002,-0.0005,0.0002,0
"Coastal",0.0011,-0.0019,0.0042,0
"Inland",0.0016,-0.0008,0.0041,0
"All",0.004,-0.0003,0.0082,0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Blaine"	-0.0005	-0.0008	-0.0002	1
"Bellingham"	-0.0005	-0.0008	-0.0001	1
"Quil"	-0.0008	-0.0017	0,0	
"Clearwater"	-0.0008	-0.0015	-0.0002	1
"Aberdeen"	-0.0008	-0.0016	0.0001	0
"Raymond"	-0.001	-0.0019	-0.0001	1
"Astoria"	-0.0008	-0.0013	-0.0002	1
"Tillamook"	-0.0008	-0.0012	-0.0004	1
"Newport"	-0.0008	-0.0014	-0.0002	1
"Florence"	-0.0005	-0.0015	0.0005	0
"North Bend"	-0.0003	-0.001	0.0005	0
"Bandon"	-0.0004	-0.001	0.0002	0
"Port"	-0.0007	-0.0016	0.0003	0
"Crescent City"	-0.0014	-0.0025	-0.0002	1
"Eureka"	-0.0002	-0.0007	0.0003	0
"Upper Mattole"	-0.0009	-0.0035	0.0017	0
"Fort Bragg"	-0.0013	-0.0026	0.0001	0
"Ukiah"	-0.0002	-0.0008	0.0004	0
"Healdsburg"	-0.0008	-0.0018	0.0003	0
"San Francisco"	0.0002	-0.0001	0.0004	0
"Santa Cruz"	-0.0007	-0.0014	0.0001	0
"Big Sur"	-0.0001	-0.0007	0.0004	0
"Paso Robles"	-0.0005	-0.0015	0.0004	0
"Santa Maria"	-0.0003	-0.0012	0.0007	0
"Santa Barbara"	-0.0008	-0.0014	-0.0002	1
"Los Angeles"	0.0003	-0.0005	0.0011	0
"Santa Ana"	-0.0004	-0.0017	0.001	0
"Escondido"	-0.0007	-0.0016	0.0002	0
"San Diego"	0.0002	-0.0002	0.0005	0
"Coastal"	-0.002	-0.0036	-0.0004	1
"Inland"	-0.0022	-0.0046	0.0001	0
"All"	-0.0043	-0.0074	-0.0012	1

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.0005, -0.0007, 0.0017, 0
 "Milwaukee WI", 0.0007, 0.0003, 0.0012, 1
 "Green Bay WI", 0.0006, 0.0001, 0.0011, 1
 "Chippewa Falls WI", 0.0004, -0.0004, 0.0011, 0
 "Medford WI", 0, -0.0006, 0.0006, 0
 "Dubuque IA", -0.0003, -0.0021, 0.0015, 0
 "Des Moines IA", 0.0007, 0.0003, 0.0012, 1
 "Cedar Rapids IA", 0.0002, -0.001, 0.0013, 0
 "Davenport IA", -0.0001, -0.0008, 0.0006, 0
 "Sioux City IA", 0.0006, 0.0001, 0.0012, 1
 "Aurora IL", 0.0005, -0.0003, 0.0012, 0
 "Denison IA", -0.0005, -0.0021, 0.001, 0
 "Spencer IA", 0.0009, -0.0003, 0.0021, 0
 "Fort Dodge IA", 0.0008, 0.0001, 0.0015, 1
 "Rockford IL", -0.0002, -0.0009, 0.0006, 0
 "Sioux Falls SD", 0.0003, -0.0008, 0.0014, 0
 "Charles City IA", 0.0011, 0.0004, 0.0018, 1
 "Hillsboro WI", -0.0003, -0.0016, 0.001, 0
 "Stevens Point WI", 0.0002, -0.0008, 0.0012, 0
 "Iron Mountain MI", 0.0003, -0.0007, 0.0014, 0
 "Park Falls WI", -0.0003, -0.0007, 0.0001, 0
 "Ashland WI", -0.0005, -0.0014, 0.0003, 0
 "Hancock-Houghton AP MI", -0.0004, -0.0011, 0.0004, 0
 "Oshkosh WI", 0.0006, -0.0002, 0.0013, 0
 "Shawano WI", -0.0008, -0.0016, 0.0001, 0
 "Spooner WI", -0.0005, -0.0014, 0.0004, 0
 "Grundy Center IA", 0.0002, -0.0018, 0.0021, 0
 "Lansing IA", 0.0011, -0.0003, 0.0025, 0
 "Rhineland WI", 0.0002, -0.0001, 0.0005, 0
 "Bergland Dam MI", -0.0001, -0.0011, 0.0008, 0
 "Alexandria", 0.0007, 0.0003, 0.001, 1
 "Beardsley", 0.001, 0.0003, 0.0018, 1
 "Canby", -0.0006, -0.0013, 0, 0
 "Crookston", 0.0007, 0.0004, 0.0011, 1
 "Duluth", -0.0002, -0.0008, 0.0004, 0
 "Fairmont", 0.0005, -0.0007, 0.0017, 0
 "Farmington", -0.0006, -0.0019, 0.0008, 0
 "Fergus_Falls", 0.0018, -0.0009, 0.0046, 0
 "Grand_Meadow", 0.0007, -0.0005, 0.0019, 0
 "Grand_Portage", -0.0001, -0.0013, 0.0012, 0
 "Hinckley", 0.0005, -0.0002, 0.0012, 0
 "International_Falls", 0.0002, -0.0001, 0.0006, 0
 "Leech_Lake", 0.0002, -0.0009, 0.0014, 0
 "Little_Falls", -0.0007, -0.0019, 0.0006, 0
 "Montevideo", 0.0002, -0.0005, 0.0008, 0
 "Moorhead", 0.0004, -0.0005, 0.0012, 0
 "Morris", 0.0003, -0.0007, 0.0012, 0
 "Park_Rapids", -0.0009, -0.0021, 0.0003, 0

"Pine_River_Dam",-0.0011,-0.0029,0.0008,0
"Pipestone",0.0009,0,0.0018,0
"Pokegama_Dam",0.0004,-0.0006,0.0015,0
"Red_Lake_Indian_Agency",0.0009,-0.0005,0.0023,0
"Redwodd_Falls",0.0009,-0.0001,0.0019,0
"St_Cloud",0.0002,-0.0005,0.0009,0
"St_Paul",0.0004,-0.0007,0.0015,0
"St_Peter",0.0016,0.0003,0.0029,1
"St_Vincent",-0.0009,-0.0022,0.0005,0
"Tower",0.0005,-0.0003,0.0013,0
"Warroad",0.0004,-0.0007,0.0015,0
"Winnibigoshish",0.0002,-0.0006,0.001,0
"Winona",0.0003,-0.0006,0.0012,0
"Coastal",0.0023,0.0001,0.0044,1
"Inland",0.0043,-0.0005,0.0092,0
"All",0.0072,0.0015,0.0128,1

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY", 0.001, -0.0007, 0.0026, 0
"Boston MA", -0.0002, -0.0009, 0.0005, 0
"Portland ME", 0.0008, 0.0002, 0.0014, 1
"Gardiner ME", 0.0009, -0.0006, 0.0024, 0
"Albany NY", 0.0005, -0.0004, 0.0013, 0
"Concord NH", 0.0006, -0.0002, 0.0015, 0
"Montreal Q", 0.0006, 0.0002, 0.001, 1
"Lakeport NH", 0.0011, 0.0001, 0.002, 1
"Burlington VT", 0.0005, 0, 0.001, 0
"Cornwall VT", 0, -0.0007, 0.0008, 0
"Northfield VT", 0.0005, -0.001, 0.0021, 0
"Corinth VT", 0.0007, 0.0003, 0.0011, 1
"Hanover NH", 0.0003, -0.0004, 0.001, 0
"Rochester NY", 0.0001, -0.0002, 0.0004, 0
"Buffalo NY", 0.0006, 0.0001, 0.001, 1
"Middletown CT", -0.0008, -0.0025, 0.0009, 0
"Ithaca NY", 0.0001, -0.0001, 0.0004, 0
"Amherst MA", 0.0004, -0.0004, 0.0012, 0
"Setauket Strong NY", -0.0003, -0.0017, 0.001, 0
"Fitchburg MA", -0.0011, -0.0018, -0.0004, 1
"Providence RI", 0.0005, -0.0001, 0.001, 0
"Waterville ME", -0.0008, -0.0017, 0.0001, 0
"Lowville NY", 0.0002, -0.0003, 0.0007, 0
"Cooperstown NY", 0.0015, 0.0006, 0.0024, 1
"Berlin NH", 0.0012, -0.0012, 0.0037, 0
"Farmington ME", 0.0005, -0.0006, 0.0016, 0
"Eastport ME", 0.0004, -0.0012, 0.0021, 0
"Coastal", 0.0024, -0.0002, 0.005, 0
"Inland", 0.0046, 0.0016, 0.0076, 1
"All", 0.0068, 0.0015, 0.0121, 1

"", "Trend", "CI-lower", "CI-upper", "Sig"
"Blaine",-0.0002,-0.0007,0.0004,0
"Bellingham",-0.0003,-0.001,0.0004,0
"Quil",-0.0002,-0.0018,0.0014,0
"Clearwater",-0.0012,-0.003,0.0005,0
"Aberdeen",0.0003,-0.0002,0.0009,0
"Raymond",-0.001,-0.0019,-0.0002,1
"Astoria",-0.0003,-0.0014,0.0008,0
"Tillamook",-0.0007,-0.0015,0.0002,0
"Newport",-0.0017,-0.0026,-0.0008,1
"Florence",0,-0.0013,0.0012,0
"North Bend",0.0002,-0.0005,0.0008,0
"Bandon",-0.0008,-0.0021,0.0004,0
"Port",-0.0019,-0.003,-0.0007,1
"Crescent City",0.0003,-0.0004,0.0009,0
"Eureka",-0.0006,-0.0015,0.0002,0
"Upper Mattole",-0.0038,-0.008,0.0005,0
"Fort Bragg",0.0004,-0.0016,0.0024,0
"Ukiah",-0.0005,-0.0019,0.0009,0
"Healdsburg",-0.0014,-0.0029,0,0
"San Francisco",0.0004,-0.0003,0.001,0
"Santa Cruz",0.0003,-0.0006,0.0013,0
"Big Sur",0.0001,-0.0015,0.0016,0
"Paso Robles",0.0005,-0.0004,0.0014,0
"Santa Maria",0.0002,-0.0008,0.0013,0
"Santa Barbara",-0.0008,-0.0028,0.0012,0
"Los Angeles",-0.0003,-0.0021,0.0016,0
"Santa Ana",-0.0018,-0.0036,0,0
"Escondido",0.0004,-0.0011,0.0019,0
"San Diego",0.0002,-0.001,0.0015,0
"Coastal",-0.0022,-0.006,0.0016,0
"Inland",-0.0056,-0.0091,-0.0021,1
"All",-0.0065,-0.0133,0.0004,0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	0.0006	-0.0004	0.0016	0
"Galveston"	0.0007	-0.0001	0.0016	0
"Shreveport"	0.0012	0.0002	0.0022	1
"Vicksburg"	0.0002	-0.003	0.0035	0
"New Orleans"	0.0007	-0.0004	0.0017	0
"Memphis"	0.0003	-0.0007	0.0013	0
"Mobile"	0.0005	-0.0009	0.002	0
"Nashville"	0.0001	-0.0006	0.0009	0
"Montgomery"	0.0005	-0.0015	0.0024	0
"Atlanta"	0.0004	-0.0003	0.0012	0
"Knoxville"	0.0008	0.0002	0.0014	1
"Macon"	0.0008	0.0003	0.0012	1
"Quitman"	-0.0013	-0.0028	0.0002	0
"Augusta"	0.0004	-0.0003	0.0011	0
"Key West"	0.0006	-0.0002	0.0015	0
"Jacksonville"	0.0006	-0.0001	0.0013	0
"Lenoir"	-0.001	-0.0018	-0.0001	1
"Savannah"	-0.0001	-0.0009	0.0006	0
"Charleston"	0.0005	-0.0006	0.0017	0
"Lynchburg"	0.0007	0	0.0014	0
"Wilmington"	0.0006	-0.0001	0.0013	0
"Weldon"	0.0022	0.0012	0.0033	1
"Washington"	0.0001	-0.0006	0.0008	0
"Norfolk"	0.0006	-0.0001	0.0014	0
"Coastal"	0.0017	0.0002	0.0031	1
"Inland"	0.0032	-0.0005	0.0069	0
"All"	0.005	0.0001	0.0098	1

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.0017, 0.001, 0.0024, 1
 "Milwaukee WI", 0.0004, -0.001, 0.0017, 0
 "Green Bay WI", 0.001, -0.0003, 0.0022, 0
 "Chippewa Falls WI", 0.0008, -0.0011, 0.0026, 0
 "Medford WI", 0, -0.0011, 0.0012, 0
 "Dubuque IA", 0.0014, 0, 0.0028, 0
 "Des Moines IA", 0.0004, -0.0008, 0.0016, 0
 "Cedar Rapids IA", 0.0014, 0.0003, 0.0024, 1
 "Davenport IA", 0.0004, -0.0012, 0.002, 0
 "Sioux City IA", 0.001, -0.0001, 0.0022, 0
 "Aurora IL", -0.0001, -0.002, 0.0019, 0
 "Denison IA", 0.0003, -0.0016, 0.0022, 0
 "Spencer IA", 0.0021, -0.0004, 0.0046, 0
 "Fort Dodge IA", 0.0005, -0.0012, 0.0021, 0
 "Rockford IL", 0.0005, -0.0003, 0.0013, 0
 "Sioux Falls SD", 0.0015, 0.0006, 0.0025, 1
 "Charles City IA", 0.0016, 0, 0.0032, 0
 "Hillsboro WI", 0.0008, -0.0008, 0.0025, 0
 "Stevens Point WI", 0.0011, 0.0003, 0.0019, 1
 "Iron Mountain MI", 0.0016, 0.0004, 0.0029, 1
 "Park Falls WI", -0.0001, -0.0012, 0.0009, 0
 "Ashland WI", -0.001, -0.0032, 0.0013, 0
 "Hancock-Houghton AP MI", -0.0008, -0.0028, 0.0013, 0
 "Oshkosh WI", 0.0001, -0.0025, 0.0028, 0
 "Shawano WI", 0.0004, -0.0008, 0.0016, 0
 "Spooner WI", -0.0002, -0.0011, 0.0007, 0
 "Grundy Center IA", 0.0021, -0.0009, 0.0052, 0
 "Lansing IA", 0.0006, -0.0036, 0.0049, 0
 "Rhinelander WI", 0.0004, -0.0006, 0.0013, 0
 "Bergland Dam MI", 0.0006, -0.0006, 0.0018, 0
 "Alexandria", 0.0004, -0.0009, 0.0017, 0
 "Beardsley", 0.0005, -0.001, 0.002, 0
 "Canby", -0.0004, -0.002, 0.0013, 0
 "Crookston", 0.0008, -0.0003, 0.002, 0
 "Duluth", 0, -0.0007, 0.0006, 0
 "Fairmont", -0.0007, -0.0021, 0.0008, 0
 "Farmington", 0.0006, -0.0023, 0.0034, 0
 "Fergus_Falls", -0.0002, -0.007, 0.0066, 0
 "Grand_Meadow", 0.0014, -0.0016, 0.0045, 0
 "Grand_Portage", -0.0003, -0.0018, 0.0012, 0
 "Hinckley", 0.0003, -0.001, 0.0017, 0
 "International_Falls", 0.0003, -0.0002, 0.0009, 0
 "Leech_Lake", -0.0011, -0.0023, 0.0002, 0
 "Little_Falls", -0.0012, -0.0046, 0.0023, 0
 "Montevideo", 0.0004, -0.0018, 0.0025, 0
 "Moorhead", 0.0003, -0.0025, 0.003, 0
 "Morris", 0.0009, 0.0001, 0.0017, 1
 "Park_Rapids", -0.0026, -0.0042, -0.0009, 1

"Pine_River_Dam",0.0007,-0.0004,0.0018,0
"Pipestone",0.0017,-0.0007,0.0041,0
"Pokegama_Dam",0.0011,-0.0016,0.0039,0
"Red_Lake_Indian_Agency",0.0001,-0.0043,0.0046,0
"Redwodd_Falls",0.0014,-0.001,0.0038,0
"St_Cloud",0.0008,-0.0005,0.002,0
"St_Paul",-0.0008,-0.0023,0.0007,0
"St_Peter",0.0019,-0.0023,0.0061,0
"St_Vincent",-0.0019,-0.0031,-0.0006,1
"Tower",0.0001,-0.0023,0.0024,0
"Warroad",-0.0011,-0.0028,0.0006,0
"Winnibigoshish",0.0003,-0.0023,0.0028,0
"Winona",0.0013,-0.0001,0.0027,0
"Coastal",0.0009,-0.0054,0.0071,0
"Inland",0.0075,-0.0048,0.0198,0
"All",0.0089,-0.0075,0.0253,0

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY",-0.0003,-0.0024,0.0019,0
"Boston MA",-0.0002,-0.0013,0.0009,0
"Portland ME",0.0012,-0.0005,0.003,0
"Gardiner ME",-0.0008,-0.0025,0.001,0
"Albany NY",0.0011,0.0002,0.002,1
"Concord NH",0.0013,-0.0006,0.0031,0
"Montreal Q",0.0011,0.0003,0.0018,1
"Lakeport NH",0.0019,0.0008,0.0029,1
"Burlington VT",0.0007,-0.0002,0.0017,0
"Cornwall VT",-0.0005,-0.0021,0.0012,0
"Northfield VT",0.0005,-0.0039,0.005,0
"Corinth VT",0.0002,-0.0009,0.0014,0
"Hanover NH",0,-0.0023,0.0022,0
"Rochester NY",0.0003,-0.0004,0.001,0
"Buffalo NY",0.0003,-0.0003,0.0009,0
"Middletown CT",-0.0018,-0.0048,0.0012,0
"Ithaca NY",0.0001,-0.0004,0.0005,0
"Amherst MA",-0.0002,-0.0011,0.0008,0
"Setauket Strong NY",-0.0005,-0.0047,0.0038,0
"Fitchburg MA",-0.0012,-0.0029,0.0005,0
"Providence RI",0.0008,-0.0006,0.0022,0
"Waterville ME",-0.0003,-0.0016,0.0009,0
"Lowville NY",0.001,0.0003,0.0017,1
"Cooperstown NY",0.0028,0.0016,0.004,1
"Berlin NH",-0.0019,-0.0041,0.0004,0
"Farmington ME",0.002,0.0004,0.0035,1
"Eastport ME",0.0021,-0.0012,0.0054,0
"Coastal",0.0028,-0.0025,0.0082,0
"Inland",0.0068,-0.0005,0.014,0
"All",0.0097,-0.0015,0.021,0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Blaine"	-0.0006	-0.0019	0.0007	0
"Bellingham"	-0.0008	-0.0027	0.0012	0
"Quil"	0.0013	-0.0002	0.0028	0
"Clearwater"	0.0004	-0.0036	0.0043	0
"Aberdeen"	0	-0.0012	0.0012	0
"Raymond"	-0.002	-0.0035	-0.0005	1
"Astoria"	0.0004	-0.0008	0.0017	0
"Tillamook"	-0.0003	-0.0017	0.0011	0
"Newport"	-0.0019	-0.0048	0.001	0
"Florence"	-0.0011	-0.0045	0.0022	0
"North Bend"	-0.0007	-0.0024	0.0011	0
"Bandon"	0.0003	-0.0014	0.002	0
"Port"	-0.0018	-0.0042	0.0006	0
"Crescent City"	-0.0002	-0.0022	0.0017	0
"Eureka"	-0.0001	-0.0017	0.0014	0
"Upper Mattole"	-0.0002	-0.0065	0.006	0
"Fort Bragg"	-0.0003	-0.0033	0.0027	0
"Ukiah"	-0.0017	-0.0053	0.002	0
"Healdsburg"	-0.0027	-0.0069	0.0015	0
"San Francisco"	-0.0004	-0.0018	0.0011	0
"Santa Cruz"	0	-0.0031	0.003	0
"Big Sur"	0.001	-0.0026	0.0045	0
"Paso Robles"	0.0013	-0.0015	0.004	0
"Santa Maria"	-0.0004	-0.0027	0.0018	0
"Santa Barbara"	-0.0013	-0.007	0.0045	0
"Los Angeles"	0.0003	-0.004	0.0046	0
"Santa Ana"	-0.0022	-0.0069	0.0024	0
"Escondido"	-0.0004	-0.0034	0.0025	0
"San Diego"	-0.0008	-0.0026	0.0009	0
"Coastal"	-0.0046	-0.0151	0.0058	0
"Inland"	-0.006	-0.0162	0.0043	0
"All"	-0.0093	-0.0291	0.0105	0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	0.0017	0	0.0033	0
"Galveston"	0.0011	-0.0008	0.003	0
"Shreveport"	0.0007	-0.0019	0.0032	0
"Vicksburg"	-0.003	-0.0049	-0.001	1
"New Orleans"	-0.0004	-0.0028	0.0021	0
"Memphis"	-0.0007	-0.0024	0.0009	0
"Mobile"	-0.001	-0.0033	0.0013	0
"Nashville"	0.0013	-0.0003	0.0029	0
"Montgomery"	-0.0021	-0.0055	0.0014	0
"Atlanta"	0.0004	-0.0018	0.0025	0
"Knoxville"	0.0016	0.0008	0.0025	1
"Macon"	0.0009	-0.0002	0.002	0
"Quitman"	-0.0026	-0.0064	0.0011	0
"Augusta"	0.0006	-0.001	0.0022	0
"Key West"	-0.0005	-0.0023	0.0012	0
"Jacksonville"	0.0014	0.0001	0.0027	1
"Lenoir"	-0.0001	-0.0011	0.001	0
"Savannah"	0.0001	-0.0023	0.0025	0
"Charleston"	0.0012	-0.0012	0.0037	0
"Lynchburg"	0.0008	-0.0007	0.0023	0
"Wilmington"	0.0004	-0.0017	0.0025	0
"Weldon"	0.0034	0.0004	0.0063	1
"Washington"	0.0011	0	0.0022	0
"Norfolk"	0.0016	0.0005	0.0027	1
"Coastal"	0.0024	-0.0015	0.0063	0
"Inland"	0.0043	-0.0041	0.0126	0
"All"	0.007	-0.0045	0.0184	0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	-0.0193	-0.0647	0.0262	0
"Galveston"	-0.0168	-0.0645	0.0308	0
"Shreveport"	0.0313	-0.0282	0.0907	0
"Vicksburg"	0.0251	-0.0191	0.0694	0
"New Orleans"	0.0442	-0.0047	0.0931	0
"Memphis"	0.0218	-0.0155	0.059	0
"Mobile"	0.0444	0.0108	0.0779	1
"Nashville"	0.0156	-0.0142	0.0454	0
"Montgomery"	0.0065	-0.0155	0.0286	0
"Atlanta"	0.0155	-0.0154	0.0465	0
"Knoxville"	0.0084	-0.0258	0.0427	0
"Macon"	-0.0298	-0.1134	0.0539	0
"Quitman"	-0.0438	-0.0972	0.0096	0
"Augusta"	0.0095	-0.0178	0.0368	0
"Key West"	0.0397	-0.0109	0.0904	0
"Jacksonville"	0.0219	-0.0134	0.0571	0
"Lenoir"	-0.0397	-0.1119	0.0324	0
"Savannah"	0.0155	-0.0098	0.0407	0
"Charleston"	0.018	-0.0637	0.0997	0
"Lynchburg"	0.0078	-0.017	0.0327	0
"Wilmington"	0.0914	-0.006	0.1888	0
"Weldon"	0.0156	-0.0653	0.0966	0
"Washington"	-0.0037	-0.0236	0.0163	0
"Norfolk"	0.0397	-0.0153	0.0948	0
"Coastal"	0.5466	-0.0855	1.1788	0
"Inland"	-0.1725	-2.0315	1.6865	0
"All"	0.9239	-2.6116	4.4595	0

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY", 0.0395, -0.0123, 0.0913, 0
"Boston MA", 0.019, -0.0014, 0.0395, 0
"Portland ME", 0.0487, 0.0156, 0.0818, 1
"Gardiner ME", 0.0311, -0.0009, 0.063, 0
"Albany NY", 0.02, 0.0026, 0.0374, 1
"Concord NH", 0.0127, -0.0149, 0.0403, 0
"Montreal Q", 0.0046, -0.0216, 0.0308, 0
"Lakeport NH", 0.0058, -0.0312, 0.0429, 0
"Burlington VT", 0.0125, -0.0035, 0.0284, 0
"Cornwall VT", 0.0148, -0.0009, 0.0306, 0
"Northfield VT", 0.0342, -0.1006, 0.1689, 0
"Corinth VT", 0.0168, -0.0028, 0.0365, 0
"Hanover NH", 0.0126, -0.004, 0.0292, 0
"Rochester NY", 0.0079, -0.0045, 0.0204, 0
"Buffalo NY", 0.0162, 0.0009, 0.0316, 1
"Middletown CT", 0.0163, -0.0303, 0.0628, 0
"Ithaca NY", 0.009, -0.0005, 0.0184, 0
"Amherst MA", 0.0158, -0.0118, 0.0435, 0
"Setauket Strong NY", 0.031, -0.0084, 0.0703, 0
"Fitchburg MA", 0.0098, -0.0118, 0.0314, 0
"Providence RI", 0.0176, -0.0382, 0.0733, 0
"Waterville ME", 0.0111, -0.0047, 0.0268, 0
"Lowville NY", 0.0143, -0.0086, 0.0371, 0
"Cooperstown NY", 0.014, -0.0335, 0.0615, 0
"Berlin NH", 0.0197, -0.0062, 0.0456, 0
"Farmington ME", 0.0277, -0.0016, 0.0569, 0
"Eastport ME", 0.0673, 0.0359, 0.0987, 1
"Coastal", 0.7511, -0.3095, 1.8117, 0
"Inland", 0.5655, -1.0144, 2.1455, 0
"All", 2.271, -3.0522, 7.5941, 0

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.0304, 0.0135, 0.0474, 1
 "Milwaukee WI", 0.0259, 0.0116, 0.0403, 1
 "Green Bay WI", 0.0074, -0.0123, 0.027, 0
 "Chippewa Falls WI", 0.0034, -0.0187, 0.0255, 0
 "Medford WI", -0.013, -0.0404, 0.0144, 0
 "Dubuque IA", 0.0306, -0.0083, 0.0695, 0
 "Des Moines IA", 0.0196, 0.0053, 0.0338, 1
 "Cedar Rapids IA", 0.0223, 0, 0.0445, 0
 "Davenport IA", 0.0288, 0.0185, 0.0391, 1
 "Sioux City IA", 0.0119, 0.0005, 0.0233, 1
 "Aurora IL", 0.0332, -0.0011, 0.0674, 0
 "Denison IA", 0.0188, 0.0013, 0.0363, 1
 "Spencer IA", 0.0104, -0.0156, 0.0364, 0
 "Fort Dodge IA", 0.0107, -0.0149, 0.0363, 0
 "Rockford IL", 0.0222, 0.002, 0.0425, 1
 "Sioux Falls SD", 0.0051, -0.0173, 0.0275, 0
 "Charles City IA", 0.0329, 0.0095, 0.0563, 1
 "Hillsboro WI", 0.0266, -0.0087, 0.0618, 0
 "Stevens Point WI", -0.0013, -0.0218, 0.0191, 0
 "Iron Mountain MI", -0.004, -0.0127, 0.0047, 0
 "Park Falls WI", -0.0134, -0.0331, 0.0063, 0
 "Ashland WI", -0.0023, -0.0173, 0.0127, 0
 "Hancock-Houghton AP MI", -0.0072, -0.0171, 0.0028, 0
 "Oshkosh WI", 0.0158, -0.0152, 0.0468, 0
 "Shawano WI", 0.0042, -0.0084, 0.0168, 0
 "Spooner WI", -0.0022, -0.027, 0.0226, 0
 "Grundy Center IA", 0.0058, -0.0162, 0.0278, 0
 "Lansing IA", 0.0265, -0.0071, 0.0602, 0
 "Rhinelander WI", 0.0105, -0.0051, 0.0261, 0
 "Bergland Dam MI", 0.0059, -0.0165, 0.0282, 0
 "Alexandria", 0.0086, -0.0099, 0.0271, 0
 "Beardsley", -0.0004, -0.0266, 0.0258, 0
 "Canby", 0.0032, -0.0099, 0.0162, 0
 "Crookston", -0.0005, -0.014, 0.013, 0
 "Duluth", 0.0134, -0.0005, 0.0273, 0
 "Fairmont", 0.0113, -0.0103, 0.0329, 0
 "Farmington", 0.0236, 0.0022, 0.045, 1
 "Fergus_Falls", 0.0071, -0.012, 0.0261, 0
 "Grand_Meadow", 0.021, -0.0233, 0.0654, 0
 "Grand_Portage", 0.009, -0.0084, 0.0264, 0
 "Hinckley", 0.0169, -0.0083, 0.0421, 0
 "International_Falls", -0.0011, -0.0094, 0.0072, 0
 "Leech_Lake", -0.0001, -0.0155, 0.0154, 0
 "Little_Falls", 0.007, -0.0081, 0.022, 0
 "Montevideo", 0.0227, 0.0087, 0.0367, 1
 "Moorhead", 0.0074, -0.0179, 0.0327, 0
 "Morris", 0.0107, 0.0002, 0.0212, 1
 "Park_Rapids", -0.0043, -0.026, 0.0173, 0

"Pine_River_Dam",-0.0091,-0.0386,0.0204,0
"Pipestone",0.0094,-0.0009,0.0197,0
"Pokegama_Dam",0.0054,-0.0154,0.0261,0
"Red_Lake_Indian_Agency",-0.0051,-0.0247,0.0145,0
"Redwodd_Falls",0.0297,-0.0093,0.0688,0
"St_Cloud",-0.0018,-0.0304,0.0268,0
"St_Paul",0.01,-0.0139,0.0339,0
"St_Peter",0.0213,0.0019,0.0406,1
"St_Vincent",0.0097,-0.0039,0.0233,0
"Tower",0.0066,-0.0025,0.0156,0
"Warroad",0.008,-0.0165,0.0325,0
"Winnibigoshish",-0.0037,-0.0241,0.0168,0
"Winona",0.007,-0.0367,0.0506,0
"Coastal",1.6411,-1.3285,4.6108,0
"Inland",2.4601,0.2914,4.6288,1
"All",7.1061,0.8257,13.3865,1

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Blaine"	-0.0036	-0.0202	0.0129	0
"Bellingham"	0.0032	-0.0054	0.0117	0
"Quil"	-0.0027	-0.0717	0.0664	0
"Clearwater"	-0.0372	-0.1014	0.0269	0
"Aberdeen"	0.0364	-0.0234	0.0962	0
"Raymond"	-0.0029	-0.0626	0.0567	0
"Astoria"	-0.0374	-0.0865	0.0118	0
"Tillamook"	-0.034	-0.0944	0.0264	0
"Newport"	-0.031	-0.0758	0.0138	0
"Florence"	-0.0081	-0.036	0.0198	0
"North Bend"	0.0166	-0.0077	0.0408	0
"Bandon"	0.0054	-0.0361	0.047	0
"Port"	-0.0207	-0.0833	0.042	0
"Crescent City"	-0.0593	-0.123	0.0044	0
"Eureka"	-0.0096	-0.0397	0.0205	0
"Upper Mattole"	-0.026	-0.1139	0.0619	0
"Fort Bragg"	0.0059	-0.0186	0.0303	0
"Ukiah"	0.0055	-0.0325	0.0435	0
"Healdsburg"	0.0078	-0.047	0.0626	0
"San Francisco"	0.011	-0.0003	0.0223	0
"Santa Cruz"	0.0172	-0.0211	0.0554	0
"Big Sur"	0.0563	0.0106	0.102	1
"Paso Robles"	-0.0028	-0.0158	0.0101	0
"Santa Maria"	0.003	-0.0085	0.0146	0
"Santa Barbara"	0.0049	-0.0243	0.0341	0
"Los Angeles"	0.0061	-0.0133	0.0255	0
"Santa Ana"	-0.0021	-0.0232	0.0191	0
"Escondido"	-0.012	-0.028	0.0041	0
"San Diego"	0.0018	-0.005	0.0086	0
"Coastal"	0.0508	-1.1695	1.2711	0
"Inland"	0.4792	-0.7498	1.7082	0
"All"	1.0245	-3.6365	5.6855	0

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.0459, 0.0081, 0.0836, 1
 "Milwaukee WI", 0.0404, 0.0067, 0.0741, 1
 "Green Bay WI", 0.0258, 0.0073, 0.0443, 1
 "Chippewa Falls WI", 0.0281, -0.0086, 0.0647, 0
 "Medford WI", 0.0064, -0.0206, 0.0334, 0
 "Dubuque IA", -0.013, -0.1288, 0.1028, 0
 "Des Moines IA", 0.037, -0.0074, 0.0814, 0
 "Cedar Rapids IA", -0.0038, -0.0427, 0.0352, 0
 "Davenport IA", 0.0356, 0.0045, 0.0668, 1
 "Sioux City IA", 0.0232, -0.0034, 0.0498, 0
 "Aurora IL", 0.0105, -0.1111, 0.1321, 0
 "Denison IA", 0.0264, -0.0208, 0.0736, 0
 "Spencer IA", 0.0433, 0.0046, 0.0819, 1
 "Fort Dodge IA", 0.0221, -0.0099, 0.054, 0
 "Rockford IL", -0.0035, -0.0376, 0.0307, 0
 "Sioux Falls SD", 0.0298, -0.0066, 0.0661, 0
 "Charles City IA", 0.0637, 0.0122, 0.1151, 1
 "Hillsboro WI", 0.0785, 0.0274, 0.1295, 1
 "Stevens Point WI", 0.0272, 0.0014, 0.0531, 1
 "Iron Mountain MI", -0.0035, -0.0243, 0.0173, 0
 "Park Falls WI", -0.0059, -0.0277, 0.0158, 0
 "Ashland WI", -0.0165, -0.0503, 0.0173, 0
 "Hancock-Houghton AP MI", -0.0059, -0.0449, 0.0331, 0
 "Oshkosh WI", 0.0583, 0.0229, 0.0937, 1
 "Shawano WI", 0.0223, -0.0078, 0.0524, 0
 "Spooner WI", -0.009, -0.0581, 0.0401, 0
 "Grundy Center IA", 0.0337, -0.0038, 0.0712, 0
 "Lansing IA", 0.0675, 0.024, 0.1111, 1
 "Rhineland WI", 0.0288, -0.0016, 0.0591, 0
 "Bergland Dam MI", -0.0235, -0.0799, 0.0328, 0
 "Alexandria", 0.0236, 0.0034, 0.0439, 1
 "Beardsley", 0.026, -0.0055, 0.0576, 0
 "Canby", 0.015, -0.0039, 0.0339, 0
 "Crookston", 0.0099, -0.0158, 0.0357, 0
 "Duluth", -0.0097, -0.0323, 0.0129, 0
 "Fairmont", 0.0178, -0.0313, 0.0668, 0
 "Farmington", 0.0356, -0.0162, 0.0875, 0
 "Fergus_Falls", 0.0286, -0.0049, 0.0621, 0
 "Grand_Meadow", 0.0695, 0.0458, 0.0932, 1
 "Grand_Portage", 0.0281, 0.0033, 0.0529, 1
 "Hinckley", 0.0348, -0.0091, 0.0786, 0
 "International_Falls", 0.0068, -0.0089, 0.0225, 0
 "Leech_Lake", -0.017, -0.0493, 0.0153, 0
 "Little_Falls", 0.0073, -0.0356, 0.0502, 0
 "Montevideo", 0.0069, -0.0439, 0.0577, 0
 "Moorhead", 0.0223, -0.0308, 0.0754, 0
 "Morris", 0.0134, -0.0197, 0.0465, 0
 "Park_Rapids", -0.028, -0.0685, 0.0125, 0

"Pine_River_Dam",0.0058,-0.0108,0.0225,0
"Pipestone",0.0109,-0.0147,0.0365,0
"Pokegama_Dam",0.0028,-0.0305,0.036,0
"Red_Lake_Indian_Agency",0.0072,-0.0517,0.066,0
"Redwodd_Falls",0.069,0.0117,0.1264,1
"St_Cloud",-0.0002,-0.042,0.0416,0
"St_Paul",0.0127,-0.0527,0.0781,0
"St_Peter",0.043,-0.0034,0.0895,0
"St_Vincent",0.0197,-0.0175,0.0569,0
"Tower",0.0171,-0.0132,0.0474,0
"Warroad",0.038,0.0012,0.0749,1
"Winnibigoshish",-0.0054,-0.0311,0.0204,0
"Winona",0.058,0.0369,0.079,1
"Coastal",1.2613,-1.6178,4.1404,0
"Inland",4.0167,-2.8973,10.9308,0
"All",8.5581,-3.3367,20.4529,0

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY", 0.0993, -0.0155, 0.214, 0
"Boston MA", -0.0295, -0.1123, 0.0533, 0
"Portland ME", 0.0697, -0.0082, 0.1477, 0
"Gardiner ME", 0.0539, 0.0155, 0.0923, 1
"Albany NY", 0.0354, -0.0066, 0.0775, 0
"Concord NH", 0.0457, -0.0063, 0.0977, 0
"Montreal Q", 0.0436, 0.0112, 0.076, 1
"Lakeport NH", 0.0621, 0.0097, 0.1144, 1
"Burlington VT", 0.0314, 0.006, 0.0567, 1
"Cornwall VT", 0.0379, 0.0075, 0.0683, 1
"Northfield VT", -0.231, -0.7022, 0.2402, 0
"Corinth VT", 0.0475, 0.0224, 0.0727, 1
"Hanover NH", 0.0266, -0.0051, 0.0584, 0
"Rochester NY", 0.0255, 0.0089, 0.0421, 1
"Buffalo NY", 0.0124, -0.018, 0.0429, 0
"Middletown CT", 0.0009, -0.1112, 0.113, 0
"Ithaca NY", 0.02, 0.0041, 0.036, 1
"Amherst MA", 0.0435, 0.0045, 0.0825, 1
"Setauket Strong NY", 0.0657, -0.0056, 0.137, 0
"Fitchburg MA", -0.0113, -0.0687, 0.0461, 0
"Providence RI", 0.0241, -0.0229, 0.0712, 0
"Waterville ME", 0.0178, -0.0081, 0.0437, 0
"Lowville NY", 0.0366, 0.0091, 0.0641, 1
"Cooperstown NY", 0.0831, 0.0167, 0.1495, 1
"Berlin NH", 0.0491, 0.0082, 0.0899, 1
"Farmington ME", 0.0563, 0.001, 0.1116, 1
"Eastport ME", 0.0876, 0.0067, 0.1684, 1
"Coastal", 1.3224, -0.6377, 3.2825, 0
"Inland", 2.1488, -0.0069, 4.3045, 0
"All", 7.232, -0.4585, 14.9226, 0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Blaine"	0.0214	0.0013	0.0415	1
"Bellingham"	0.0003	-0.0298	0.0304	0
"Quil"	0.0713	-0.0093	0.152	0
"Clearwater"	-0.0731	-0.2869	0.1407	0
"Aberdeen"	0.1125	0.0415	0.1835	1
"Raymond"	0.044	-0.0552	0.1431	0
"Astoria"	0.027	-0.0558	0.1097	0
"Tillamook"	0.0199	-0.0469	0.0868	0
"Newport"	-0.0996	-0.1727	-0.0265	1
"Florence"	-0.0151	-0.0686	0.0384	0
"North Bend"	0.0257	-0.0464	0.0979	0
"Bandon"	-0.0521	-0.0976	-0.0067	1
"Port"	-0.0958	-0.1626	-0.029	1
"Crescent City"	-0.0164	-0.17	0.1373	0
"Eureka"	-0.0126	-0.0679	0.0428	0
"Upper Mattole"	-0.0349	-0.2994	0.2296	0
"Fort Bragg"	-0.0004	-0.0514	0.0506	0
"Ukiah"	-0.0342	-0.0916	0.0231	0
"Healdsburg"	-0.0478	-0.1181	0.0226	0
"San Francisco"	0.0202	-0.0111	0.0516	0
"Santa Cruz"	-0.0084	-0.0619	0.0451	0
"Big Sur"	0.0064	-0.0867	0.0995	0
"Paso Robles"	0.0081	-0.018	0.0342	0
"Santa Maria"	0.0149	-0.0081	0.038	0
"Santa Barbara"	0.0166	-0.0493	0.0824	0
"Los Angeles"	-0.0009	-0.0411	0.0392	0
"Santa Ana"	-0.0132	-0.04	0.0136	0
"Escondido"	0.0082	-0.024	0.0403	0
"San Diego"	0.0078	-0.0089	0.0246	0
"Coastal"	-1.1791	-3.5399	1.1817	0
"Inland"	-1.2568	-4.2393	1.7257	0
"All"	-5.0108	-14.4478	4.4262	0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	0.0522	-0.0025	0.1069	0
"Galveston"	0.0712	-0.045	0.1874	0
"Shreveport"	0.0982	-0.0336	0.2301	0
"Vicksburg"	0.0338	-0.1129	0.1804	0
"New Orleans"	0.1003	-0.009	0.2096	0
"Memphis"	0.0603	-0.0103	0.1308	0
"Mobile"	0.0639	-0.0853	0.2131	0
"Nashville"	0.0309	-0.0258	0.0876	0
"Montgomery"	0.0104	-0.0744	0.0951	0
"Atlanta"	0.0705	0.0219	0.119	1
"Knoxville"	0.0595	0.0085	0.1105	1
"Macon"	0.0734	0.028	0.1189	1
"Quitman"	0.0302	-0.0563	0.1167	0
"Augusta"	0.0624	-0.0064	0.1313	0
"Key West"	-0.0294	-0.2042	0.1455	0
"Jacksonville"	0.0028	-0.0694	0.0749	0
"Lenoir"	0.0222	-0.0576	0.102	0
"Savannah"	0.0221	-0.065	0.1093	0
"Charleston"	0.0805	-0.0314	0.1924	0
"Lynchburg"	0.0534	0.0129	0.094	1
"Wilmington"	0.1795	0.0356	0.3235	1
"Weldon"	0.1153	0.0375	0.1931	1
"Washington"	0.019	-0.0585	0.0966	0
"Norfolk"	0.0766	-0.0572	0.2104	0
"Coastal"	1.2245	0.5258	1.9232	1
"Inland"	1.8818	-0.2504	4.014	0
"All"	4.9332	1.0692	8.7972	1

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.079, 0.0091, 0.1489, 1
 "Milwaukee WI", 0.0003, -0.081, 0.0817, 0
 "Green Bay WI", 0.0319, -0.029, 0.0928, 0
 "Chippewa Falls WI", 0.0381, -0.0288, 0.1049, 0
 "Medford WI", 0.0058, -0.0623, 0.0739, 0
 "Dubuque IA", 0.0928, -0.0144, 0.2001, 0
 "Des Moines IA", 0.0171, -0.0743, 0.1086, 0
 "Cedar Rapids IA", 0.0065, -0.06, 0.073, 0
 "Davenport IA", 0.0063, -0.0831, 0.0957, 0
 "Sioux City IA", 0.0463, -0.0255, 0.1181, 0
 "Aurora IL", -0.0681, -0.3986, 0.2624, 0
 "Denison IA", 0.0123, -0.1282, 0.1527, 0
 "Spencer IA", 0.0675, -0.0415, 0.1765, 0
 "Fort Dodge IA", 0.0219, -0.0827, 0.1265, 0
 "Rockford IL", 0.0228, -0.0427, 0.0883, 0
 "Sioux Falls SD", 0.0685, 0.0114, 0.1256, 1
 "Charles City IA", 0.1209, -0.0106, 0.2524, 0
 "Hillsboro WI", 0.1306, 0.0101, 0.251, 1
 "Stevens Point WI", 0.0425, -0.0298, 0.1148, 0
 "Iron Mountain MI", 0.0111, -0.0275, 0.0496, 0
 "Park Falls WI", 0.0074, -0.0416, 0.0564, 0
 "Ashland WI", -0.0021, -0.0719, 0.0677, 0
 "Hancock-Houghton AP MI", 0.0067, -0.0826, 0.096, 0
 "Oshkosh WI", 0.0466, -0.0884, 0.1816, 0
 "Shawano WI", 0.0366, -0.0534, 0.1266, 0
 "Spooner WI", -0.0403, -0.0949, 0.0143, 0
 "Grundy Center IA", 0.0621, -0.0447, 0.169, 0
 "Lansing IA", 0.0783, -0.0179, 0.1745, 0
 "Rhineland WI", 0.0351, -0.069, 0.1393, 0
 "Bergland Dam MI", 0.0112, -0.0366, 0.059, 0
 "Alexandria", 0.0127, -0.0472, 0.0726, 0
 "Beardsley", 0.0305, -0.0438, 0.1048, 0
 "Canby", 0.0116, -0.0419, 0.0651, 0
 "Crookston", 0.0032, -0.0814, 0.0877, 0
 "Duluth", -0.0101, -0.0672, 0.0471, 0
 "Fairmont", -0.0207, -0.147, 0.1055, 0
 "Farmington", 0.0542, -0.0326, 0.1409, 0
 "Fergus_Falls", 0.0251, -0.0498, 0.1, 0
 "Grand_Meadow", 0.0734, 0.0022, 0.1446, 1
 "Grand_Portage", 0.0394, -0.0068, 0.0856, 0
 "Hinckley", 0.0638, -0.0237, 0.1513, 0
 "International_Falls", 0.0216, -0.0083, 0.0516, 0
 "Leech_Lake", -0.0152, -0.0523, 0.022, 0
 "Little_Falls", 0.0396, -0.012, 0.0912, 0
 "Montevideo", 0.0021, -0.0839, 0.088, 0
 "Moorhead", -0.0018, -0.1646, 0.161, 0
 "Morris", 0.033, -0.0288, 0.0947, 0
 "Park_Rapids", -0.087, -0.1724, -0.0017, 1

"Pine_River_Dam",0.0181,-0.0242,0.0605,0
"Pipestone",0.0188,-0.0404,0.078,0
"Pokegama_Dam",-0.039,-0.0908,0.0128,0
"Red_Lake_Indian_Agency",-0.0336,-0.1926,0.1253,0
"Redwodd_Falls",0.095,-0.0538,0.2439,0
"St_Cloud",0.0223,-0.0599,0.1046,0
"St_Paul",-0.0537,-0.1183,0.0109,0
"St_Peter",0.0565,-0.0874,0.2004,0
"St_Vincent",0.0297,-0.0718,0.1312,0
"Tower",0.0093,-0.0614,0.0799,0
"Warroad",0.003,-0.0906,0.0966,0
"Winnibigoshish",-0.0335,-0.0729,0.0059,0
"Winona",0.0884,0.0392,0.1376,1
"Coastal",0.5832,-7.3897,8.556,0
"Inland",11.973,0.1129,23.8331,1
"All",20.2489,-5.5945,46.0923,0

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY", 0.067, -0.119, 0.253, 0
"Boston MA", -0.0412, -0.1489, 0.0665, 0
"Portland ME", 0.0372, -0.1982, 0.2725, 0
"Gardiner ME", 0.0724, -0.0172, 0.162, 0
"Albany NY", 0.0668, -0.0324, 0.1661, 0
"Concord NH", 0.0658, -0.0604, 0.192, 0
"Montreal Q", 0.077, 0.01, 0.144, 1
"Lakeport NH", 0.0748, -0.0416, 0.1911, 0
"Burlington VT", 0.0355, -0.01, 0.0811, 0
"Cornwall VT", 0.0305, -0.0414, 0.1024, 0
"Northfield VT", 0.0179, -0.0522, 0.088, 0
"Corinth VT", 0.0504, -0.0096, 0.1104, 0
"Hanover NH", 0.0002, -0.0937, 0.0941, 0
"Rochester NY", 0.0219, -0.0222, 0.0661, 0
"Buffalo NY", -0.0028, -0.0607, 0.0551, 0
"Middletown CT", -0.0827, -0.2236, 0.0581, 0
"Ithaca NY", 0.0175, -0.0318, 0.0667, 0
"Amherst MA", 0.0406, -0.0497, 0.1309, 0
"Setauket Strong NY", 0.1444, 0.0022, 0.2867, 1
"Fitchburg MA", -0.0616, -0.1362, 0.0131, 0
"Providence RI", 0.0482, -0.0783, 0.1747, 0
"Waterville ME", 0.0265, -0.0375, 0.0904, 0
"Lowville NY", 0.0674, -0.006, 0.1409, 0
"Cooperstown NY", 0.1576, -0.0173, 0.3325, 0
"Berlin NH", 0.0043, -0.0728, 0.0814, 0
"Farmington ME", 0.1033, -0.0478, 0.2544, 0
"Eastport ME", 0.1778, -0.0071, 0.3627, 0
"Coastal", 1.4086, -2.2174, 5.0347, 0
"Inland", 2.3959, -3.5585, 8.3504, 0
"All", 7.5641, -10.5967, 25.7249, 0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Blaine"	0.0332	-0.0225	0.0889	0
"Bellingham"	-0.0328	-0.1084	0.0427	0
"Quil"	0.1261	-0.0275	0.2798	0
"Clearwater"	0.1119	-0.2614	0.4852	0
"Aberdeen"	0.0301	-0.1188	0.1791	0
"Raymond"	0.0403	-0.1064	0.187	0
"Astoria"	0.0839	-0.017	0.1848	0
"Tillamook"	0.046	-0.1691	0.2611	0
"Newport"	-0.1341	-0.3586	0.0904	0
"Florence"	-0.0369	-0.2086	0.1347	0
"North Bend"	-0.0806	-0.2171	0.0559	0
"Bandon"	-0.0487	-0.1637	0.0663	0
"Port"	-0.1214	-0.3172	0.0744	0
"Crescent City"	0.1116	-0.0801	0.3032	0
"Eureka"	-0.0181	-0.1627	0.1266	0
"Upper Mattole"	0.0458	-0.5149	0.6066	0
"Fort Bragg"	0.0052	-0.1276	0.138	0
"Ukiah"	-0.0623	-0.2373	0.1127	0
"Healdsburg"	-0.1258	-0.3534	0.1017	0
"San Francisco"	-0.009	-0.0926	0.0745	0
"Santa Cruz"	-0.0427	-0.2047	0.1193	0
"Big Sur"	0.0025	-0.3027	0.3078	0
"Paso Robles"	0.0255	-0.0456	0.0965	0
"Santa Maria"	0.0105	-0.0576	0.0785	0
"Santa Barbara"	0.0347	-0.2166	0.286	0
"Los Angeles"	0.0274	-0.0831	0.1379	0
"Santa Ana"	-0.0199	-0.0943	0.0545	0
"Escondido"	0.0092	-0.058	0.0763	0
"San Diego"	-0.0019	-0.0301	0.0264	0
"Coastal"	-3.6174	-9.9246	2.6898	0
"Inland"	-0.6612	-8.4993	7.177	0
"All"	-9.0424	-36.1885	18.1036	0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	0.0753	-0.094	0.2447	0
"Galveston"	0.1041	-0.2129	0.421	0
"Shreveport"	-0.0094	-0.3106	0.2919	0
"Vicksburg"	-0.1186	-0.3316	0.0944	0
"New Orleans"	0.0054	-0.2104	0.2212	0
"Memphis"	0.007	-0.1102	0.1241	0
"Mobile"	0.0043	-0.3435	0.3521	0
"Nashville"	0.0974	-0.0558	0.2507	0
"Montgomery"	-0.0625	-0.2951	0.1702	0
"Atlanta"	0.0753	-0.0833	0.2338	0
"Knoxville"	0.1298	0.042	0.2177	1
"Macon"	0.0824	-0.06	0.2248	0
"Quitman"	0.0094	-0.2032	0.222	0
"Augusta"	0.0905	-0.098	0.279	0
"Key West"	-0.3509	-1.0632	0.3613	0
"Jacksonville"	0.061	-0.134	0.256	0
"Lenoir"	0.1217	0.0086	0.2348	1
"Savannah"	0.0967	-0.1751	0.3684	0
"Charleston"	0.1776	-0.0523	0.4075	0
"Lynchburg"	0.0938	-0.007	0.1946	0
"Wilmington"	0.2717	-0.051	0.5944	0
"Weldon"	0.1623	-0.0903	0.415	0
"Washington"	0.1346	0.0358	0.2335	1
"Norfolk"	0.2053	-0.0604	0.471	0
"Coastal"	1.7223	-0.3106	3.7552	0
"Inland"	1.3538	-3.088	5.7955	0
"All"	3.6716	-3.7863	11.1296	0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	-0.0041	-0.0134	0.0051	0
"Galveston"	-0.0031	-0.0112	0.0049	0
"Shreveport"	0.0013	-0.0074	0.01	0
"Vicksburg"	0.0044	0.0003	0.0086	1
"New Orleans"	0.0025	-0.0058	0.0109	0
"Memphis"	-0.001	-0.0065	0.0045	0
"Mobile"	0.0051	-0.0003	0.0105	0
"Nashville"	0.0015	-0.0035	0.0066	0
"Montgomery"	-0.0004	-0.0075	0.0067	0
"Atlanta"	0.0023	-0.0022	0.0067	0
"Knoxville"	0.0013	-0.0011	0.0036	0
"Macon"	-0.0052	-0.0167	0.0062	0
"Quitman"	-0.0059	-0.0147	0.0029	0
"Augusta"	0.0035	-0.0011	0.0081	0
"Key West"	0.0066	-0.0025	0.0157	0
"Jacksonville"	0.004	-0.0033	0.0113	0
"Lenoir"	-0.0059	-0.0167	0.0048	0
"Savannah"	0.0019	-0.0034	0.0073	0
"Charleston"	0.0037	-0.0024	0.0098	0
"Lynchburg"	0.0023	-0.0018	0.0063	0
"Wilmington"	0.0114	-0.0022	0.0251	0
"Weldon"	0.0033	-0.0115	0.0182	0
"Washington"	0	-0.0061	0.0061	0
"Norfolk"	0.0101	0.001	0.0192	1
"Coastal"	0.0139	0.0035	0.0243	1
"Inland"	-0.0052	-0.0268	0.0164	0
"All"	0.0082	-0.0114	0.0278	0

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY", 0.0065, -0.0018, 0.0147, 0
"Boston MA", 0.0021, -0.0034, 0.0076, 0
"Portland ME", 0.008, 0.0031, 0.013, 1
"Gardiner ME", 0.0058, 0.0001, 0.0114, 1
"Albany NY", 0.0025, -0.0028, 0.0079, 0
"Concord NH", -0.0004, -0.0048, 0.0039, 0
"Montreal Q", 0.0005, -0.0036, 0.0046, 0
"Lakeport NH", -0.0002, -0.0054, 0.0051, 0
"Burlington VT", 0.0018, -0.0008, 0.0044, 0
"Cornwall VT", 0.003, -0.0002, 0.0061, 0
"Northfield VT", 0.0036, -0.0096, 0.0168, 0
"Corinth VT", 0.0012, -0.0022, 0.0046, 0
"Hanover NH", 0.0003, -0.0028, 0.0033, 0
"Rochester NY", 0.0016, -0.0027, 0.0059, 0
"Buffalo NY", 0.0022, -0.0017, 0.0061, 0
"Middletown CT", 0.0042, -0.0024, 0.0108, 0
"Ithaca NY", 0.001, -0.0017, 0.0036, 0
"Amherst MA", 0.0014, -0.0035, 0.0063, 0
"Setauket Strong NY", 0.0053, -0.0014, 0.012, 0
"Fitchburg MA", -0.0007, -0.0047, 0.0033, 0
"Providence RI", 0.0021, -0.0048, 0.0091, 0
"Waterville ME", 0.0019, -0.0011, 0.005, 0
"Lowville NY", 0.0039, -0.0013, 0.0091, 0
"Cooperstown NY", 0.0035, -0.0045, 0.0115, 0
"Berlin NH", 0.0038, -0.0009, 0.0085, 0
"Farmington ME", 0.0031, -0.0009, 0.0071, 0
"Eastport ME", 0.0107, 0.0058, 0.0157, 1
"Coastal", -0.0012, -0.0234, 0.0209, 0
"Inland", -0.002, -0.0223, 0.0182, 0
"All", -0.011, -0.0526, 0.0306, 0

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.0051, 0.002, 0.0082, 1
 "Milwaukee WI", 0.006, 0.0016, 0.0104, 1
 "Green Bay WI", 0.0006, -0.0024, 0.0036, 0
 "Chippewa Falls WI", 0.0016, -0.0038, 0.007, 0
 "Medford WI", -0.0019, -0.0062, 0.0023, 0
 "Dubuque IA", 0.0047, -0.0037, 0.0131, 0
 "Des Moines IA", 0.0031, -0.0007, 0.0068, 0
 "Cedar Rapids IA", 0.0026, -0.0036, 0.0089, 0
 "Davenport IA", 0.0037, -0.0001, 0.0076, 0
 "Sioux City IA", 0.0025, -0.0011, 0.0062, 0
 "Aurora IL", 0.0073, -0.0008, 0.0155, 0
 "Denison IA", 0.0023, -0.0014, 0.0059, 0
 "Spencer IA", 0.0011, -0.0033, 0.0055, 0
 "Fort Dodge IA", -0.0008, -0.0054, 0.0037, 0
 "Rockford IL", 0.0052, 0.0003, 0.0101, 1
 "Sioux Falls SD", 0.0038, -0.0003, 0.0079, 0
 "Charles City IA", 0.006, 0.0017, 0.0102, 1
 "Hillsboro WI", 0.0058, -0.0032, 0.0147, 0
 "Stevens Point WI", 0.0019, -0.0015, 0.0053, 0
 "Iron Mountain MI", -0.0018, -0.0041, 0.0005, 0
 "Park Falls WI", -0.0031, -0.0083, 0.0021, 0
 "Ashland WI", 0, -0.0042, 0.0041, 0
 "Hancock-Houghton AP MI", -0.0008, -0.0055, 0.0039, 0
 "Oshkosh WI", 0.0031, -0.0015, 0.0076, 0
 "Shawano WI", -0.0009, -0.0054, 0.0035, 0
 "Spooner WI", -0.0016, -0.007, 0.0038, 0
 "Grundy Center IA", 0.0009, -0.0038, 0.0057, 0
 "Lansing IA", 0.0048, -0.0009, 0.0105, 0
 "Rhinelander WI", 0.0039, 0.0003, 0.0074, 1
 "Bergland Dam MI", -0.0004, -0.0094, 0.0086, 0
 "Alexandria", 0.0037, -0.0014, 0.0088, 0
 "Beardsley", -0.0001, -0.0046, 0.0045, 0
 "Canby", 0.0014, -0.0022, 0.0051, 0
 "Crookston", -0.0002, -0.0037, 0.0034, 0
 "Duluth", 0.0023, -0.0017, 0.0063, 0
 "Fairmont", 0.0047, 0.0008, 0.0087, 1
 "Farmington", 0.003, -0.0021, 0.008, 0
 "Fergus_Falls", -0.0012, -0.0054, 0.0029, 0
 "Grand_Meadow", 0.0057, -0.0054, 0.0168, 0
 "Grand_Portage", 0.0008, -0.0032, 0.0048, 0
 "Hinckley", 0.0055, 0, 0.0109, 0
 "International_Falls", 0.0019, -0.0015, 0.0052, 0
 "Leech_Lake", 0.0007, -0.0049, 0.0062, 0
 "Little_Falls", 0.0011, -0.003, 0.0051, 0
 "Montevideo", 0.005, 0.0006, 0.0095, 1
 "Moorhead", 0.0018, -0.0028, 0.0064, 0
 "Morris", 0.0026, -0.0015, 0.0067, 0
 "Park_Rapids", 0.001, -0.0055, 0.0074, 0

"Pine_River_Dam",-0.0026,-0.0114,0.0062,0
"Pipestone",0.0024,-0.0014,0.0063,0
"Pokegama_Dam",0.002,-0.0019,0.006,0
"Red_Lake_Indian_Agency",0.0008,-0.0031,0.0046,0
"Redwodd_Falls",0.0079,-0.0047,0.0205,0
"St_Cloud",-0.0001,-0.0066,0.0064,0
"St_Paul",0.0008,-0.0053,0.0069,0
"St_Peter",0.0047,0.0001,0.0092,1
"St_Vincent",0.0037,-0.0008,0.0083,0
"Tower",0.0015,-0.0018,0.0049,0
"Warroad",0.0019,-0.0047,0.0086,0
"Winnibigoshish",-0.0025,-0.0079,0.0029,0
"Winona",0.0013,-0.0103,0.013,0
"Coastal",0.0209,-0.0187,0.0605,0
"Inland",0.0117,-0.0042,0.0277,0
"All",0.0237,-0.0102,0.0576,0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Blaine"	0.0014	-0.005	0.0078	0
"Bellingham"	0.0009	-0.0022	0.004	0
"Quil"	0.0016	-0.0058	0.0091	0
"Clearwater"	-0.003	-0.0148	0.0088	0
"Aberdeen"	0.0085	0.0012	0.0157	1
"Raymond"	0.0028	-0.009	0.0146	0
"Astoria"	-0.0028	-0.0127	0.0071	0
"Tillamook"	-0.0028	-0.0147	0.0091	0
"Newport"	-0.0049	-0.0083	-0.0015	1
"Florence"	-0.0034	-0.007	0.0003	0
"North Bend"	0.0021	-0.0017	0.0059	0
"Bandon"	-0.0012	-0.0116	0.0091	0
"Port"	-0.0004	-0.0074	0.0066	0
"Crescent City"	-0.0038	-0.0112	0.0037	0
"Eureka"	-0.0041	-0.0084	0.0003	0
"Upper Mattole"	-0.0049	-0.0112	0.0014	0
"Fort Bragg"	0.0004	-0.0028	0.0036	0
"Ukiah"	0.0017	-0.0038	0.0073	0
"Healdsburg"	0.0012	-0.0052	0.0075	0
"San Francisco"	0.0046	-0.001	0.0102	0
"Santa Cruz"	0.0041	-0.0025	0.0107	0
"Big Sur"	0.0107	0.0049	0.0166	1
"Paso Robles"	-0.0001	-0.0044	0.0042	0
"Santa Maria"	0.0002	-0.0031	0.0036	0
"Santa Barbara"	-0.0006	-0.0064	0.0053	0
"Los Angeles"	0.0001	-0.0063	0.0065	0
"Santa Ana"	-0.0028	-0.0087	0.0032	0
"Escondido"	-0.0038	-0.0087	0.0011	0
"San Diego"	0.0003	-0.0027	0.0033	0
"Coastal"	-0.0006	-0.024	0.0228	0
"Inland"	0.0068	-0.0143	0.0279	0
"All"	0.011	-0.0377	0.0597	0

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.0047, -0.0036, 0.013, 0
 "Milwaukee WI", 0.0111, 0.002, 0.0202, 1
 "Green Bay WI", 0, -0.0081, 0.008, 0
 "Chippewa Falls WI", 0.0088, -0.001, 0.0187, 0
 "Medford WI", -0.003, -0.0127, 0.0066, 0
 "Dubuque IA", -0.0057, -0.0307, 0.0193, 0
 "Des Moines IA", 0.0088, -0.0037, 0.0212, 0
 "Cedar Rapids IA", -0.0037, -0.0147, 0.0073, 0
 "Davenport IA", 0.0027, -0.0087, 0.0141, 0
 "Sioux City IA", -0.002, -0.013, 0.0089, 0
 "Aurora IL", -0.0041, -0.028, 0.0199, 0
 "Denison IA", 0.0014, -0.0116, 0.0143, 0
 "Spencer IA", 0.0061, -0.0043, 0.0165, 0
 "Fort Dodge IA", 0.0009, -0.0077, 0.0095, 0
 "Rockford IL", -0.0026, -0.0161, 0.011, 0
 "Sioux Falls SD", 0.0067, -0.0055, 0.0188, 0
 "Charles City IA", 0.0103, -0.0044, 0.0251, 0
 "Hillsboro WI", 0.0195, 0.0104, 0.0285, 1
 "Stevens Point WI", 0.0046, -0.0018, 0.0111, 0
 "Iron Mountain MI", -0.0019, -0.0077, 0.0039, 0
 "Park Falls WI", -0.0038, -0.0118, 0.0042, 0
 "Ashland WI", -0.0026, -0.0105, 0.0053, 0
 "Hancock-Houghton AP MI", 0.0038, -0.0065, 0.0141, 0
 "Oshkosh WI", 0.0091, -0.0009, 0.0191, 0
 "Shawano WI", 0.0056, -0.0029, 0.014, 0
 "Spooner WI", -0.0035, -0.021, 0.0139, 0
 "Grundy Center IA", 0.0047, -0.0076, 0.017, 0
 "Lansing IA", 0.0109, 0.0031, 0.0188, 1
 "Rhineland WI", 0.0069, -0.0045, 0.0183, 0
 "Bergland Dam MI", -0.0143, -0.0299, 0.0014, 0
 "Alexandria", 0.0093, 0.0041, 0.0146, 1
 "Beardsley", 0.0044, -0.0047, 0.0134, 0
 "Canby", 0.0029, -0.0042, 0.0099, 0
 "Crookston", 0.0018, -0.0043, 0.008, 0
 "Duluth", -0.0025, -0.011, 0.0059, 0
 "Fairmont", 0.0015, -0.0131, 0.016, 0
 "Farmington", 0.0043, -0.0123, 0.0209, 0
 "Fergus_Falls", 0.0029, -0.0054, 0.0111, 0
 "Grand_Meadow", 0.0189, 0.0093, 0.0286, 1
 "Grand_Portage", 0.0028, -0.0029, 0.0086, 0
 "Hinckley", 0.0098, -0.0033, 0.0229, 0
 "International_Falls", -0.0002, -0.0082, 0.0079, 0
 "Leech_Lake", -0.0099, -0.0211, 0.0013, 0
 "Little_Falls", 0, -0.0116, 0.0117, 0
 "Montevideo", 0.0024, -0.0115, 0.0163, 0
 "Moorhead", 0.0026, -0.0138, 0.019, 0
 "Morris", 0.0003, -0.0151, 0.0158, 0
 "Park_Rapids", -0.0039, -0.0204, 0.0125, 0

"Pine_River_Dam",0.0037,-0.0017,0.0092,0
"Pipestone",-0.0014,-0.0148,0.012,0
"Pokegama_Dam",-0.0007,-0.0095,0.0081,0
"Red_Lake_Indian_Agency",0.0023,-0.0117,0.0163,0
"Redwodd_Falls",0.0196,0.0042,0.035,1
"St_Cloud",-0.0051,-0.0133,0.0031,0
"St_Paul",0.0006,-0.0157,0.0168,0
"St_Peter",0.009,-0.0043,0.0224,0
"St_Vincent",0.0036,-0.0128,0.02,0
"Tower",0.0023,-0.0077,0.0124,0
"Warroad",0.0119,0.0032,0.0207,1
"Winnibigoshish",-0.0051,-0.0128,0.0025,0
"Winona",0.0148,0.0082,0.0215,1
"Coastal",-0.0008,-0.0616,0.0601,0
"Inland",0.0156,-0.0429,0.0741,0
"All",0.0353,-0.0734,0.1439,0

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY", 0.0154, -0.0011, 0.032, 0
"Boston MA", -0.0052, -0.0269, 0.0164, 0
"Portland ME", 0.0063, -0.0125, 0.025, 0
"Gardiner ME", 0.0111, 0.0033, 0.0189, 1
"Albany NY", 0.0095, -0.0017, 0.0206, 0
"Concord NH", 0.0054, -0.0023, 0.0132, 0
"Montreal Q", 0.0055, -0.0016, 0.0126, 0
"Lakeport NH", 0.0045, -0.0074, 0.0163, 0
"Burlington VT", 0.0042, -0.0016, 0.01, 0
"Cornwall VT", 0.0065, -0.0016, 0.0146, 0
"Northfield VT", -0.0212, -0.0693, 0.027, 0
"Corinth VT", 0.0052, -0.0014, 0.0118, 0
"Hanover NH", -0.0004, -0.0074, 0.0066, 0
"Rochester NY", 0.0069, 0.0018, 0.012, 1
"Buffalo NY", 0, -0.0101, 0.0101, 0
"Middletown CT", 0.0046, -0.0113, 0.0206, 0
"Ithaca NY", 0.0002, -0.0074, 0.0078, 0
"Amherst MA", 0.0059, -0.0056, 0.0174, 0
"Setauket Strong NY", 0.0104, -0.0038, 0.0245, 0
"Fitchburg MA", -0.0008, -0.0137, 0.012, 0
"Providence RI", -0.0014, -0.013, 0.0103, 0
"Waterville ME", 0.0023, -0.0072, 0.0119, 0
"Lowville NY", 0.0108, 0.0028, 0.0188, 1
"Cooperstown NY", 0.0137, -0.0042, 0.0316, 0
"Berlin NH", 0.0081, -0.0067, 0.0229, 0
"Farmington ME", 0.0078, -0.0001, 0.0156, 0
"Eastport ME", 0.0159, 0.0045, 0.0272, 1
"Coastal", 0.0149, -0.0506, 0.0804, 0
"Inland", 0.0216, -0.0178, 0.061, 0
"All", 0.0283, -0.0739, 0.1306, 0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Blaine"	0.0105	0.0032	0.0178	1
"Bellingham"	0.0009	-0.0107	0.0125	0
"Quil"	0.0091	-0.0025	0.0207	0
"Clearwater"	-0.0129	-0.0462	0.0205	0
"Aberdeen"	0.0186	0.0039	0.0333	1
"Raymond"	0.0171	0.0026	0.0316	1
"Astoria"	0.013	0.0061	0.02	1
"Tillamook"	0.0097	0.0015	0.0179	1
"Newport"	-0.0074	-0.014	-0.0007	1
"Florence"	-0.0052	-0.0146	0.0042	0
"North Bend"	0.0015	-0.0095	0.0125	0
"Bandon"	-0.0151	-0.0233	-0.0068	1
"Port"	-0.006	-0.0196	0.0077	0
"Crescent City"	-0.0036	-0.0299	0.0226	0
"Eureka"	-0.0072	-0.0199	0.0056	0
"Upper Mattole"	-0.005	-0.0219	0.0118	0
"Fort Bragg"	-0.0002	-0.0079	0.0075	0
"Ukiah"	-0.005	-0.0164	0.0065	0
"Healdsburg"	-0.0037	-0.0151	0.0077	0
"San Francisco"	0.0111	0.0018	0.0204	1
"Santa Cruz"	0.0003	-0.0102	0.0109	0
"Big Sur"	0.007	-0.0106	0.0246	0
"Paso Robles"	0.0033	-0.0054	0.0121	0
"Santa Maria"	0.0047	-0.0028	0.0123	0
"Santa Barbara"	0.002	-0.01	0.014	0
"Los Angeles"	-0.002	-0.0132	0.0092	0
"Santa Ana"	-0.0056	-0.0112	-0.0001	1
"Escondido"	0.0027	-0.0063	0.0116	0
"San Diego"	0.0034	-0.0038	0.0105	0
"Coastal"	-0.0239	-0.0536	0.0057	0
"Inland"	-0.0204	-0.0639	0.0231	0
"All"	-0.0519	-0.1162	0.0124	0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	0.0105	-0.0025	0.0235	0
"Galveston"	-0.0036	-0.0294	0.0222	0
"Shreveport"	0.0073	-0.0137	0.0284	0
"Vicksburg"	0.0045	-0.0115	0.0206	0
"New Orleans"	0.0125	-0.0038	0.0289	0
"Memphis"	0.0113	-0.0013	0.0238	0
"Mobile"	0.0096	-0.0098	0.0291	0
"Nashville"	0.0051	-0.0054	0.0156	0
"Montgomery"	-0.0074	-0.0222	0.0075	0
"Atlanta"	0.0089	0.0015	0.0162	1
"Knoxville"	0.0047	-0.0045	0.014	0
"Macon"	0.0064	-0.0047	0.0175	0
"Quitman"	0.0071	-0.0059	0.0201	0
"Augusta"	0.0131	0.0042	0.0219	1
"Key West"	-0.0026	-0.0281	0.023	0
"Jacksonville"	-0.0094	-0.0279	0.0091	0
"Lenoir"	0.0041	-0.0104	0.0187	0
"Savannah"	0.0083	-0.0118	0.0284	0
"Charleston"	0.012	-0.0058	0.0298	0
"Lynchburg"	0.0091	0.0005	0.0177	1
"Wilmington"	0.0211	-0.0125	0.0547	0
"Weldon"	0.0238	0.0048	0.0427	1
"Washington"	-0.0041	-0.0272	0.0189	0
"Norfolk"	0.015	-0.012	0.0421	0
"Coastal"	0.0244	-0.0077	0.0564	0
"Inland"	0.0139	-0.025	0.0528	0
"All"	0.039	0.0032	0.0748	1

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.0076, -0.0161, 0.0312, 0
 "Milwaukee WI", 0.0055, -0.0175, 0.0284, 0
 "Green Bay WI", 0.0034, -0.0175, 0.0243, 0
 "Chippewa Falls WI", 0.0079, -0.0086, 0.0243, 0
 "Medford WI", -0.0013, -0.0154, 0.0129, 0
 "Dubuque IA", 0.0178, -0.0181, 0.0538, 0
 "Des Moines IA", 0.0101, -0.0092, 0.0295, 0
 "Cedar Rapids IA", -0.0041, -0.0266, 0.0185, 0
 "Davenport IA", -0.0129, -0.0365, 0.0107, 0
 "Sioux City IA", 0.0111, -0.0076, 0.0299, 0
 "Aurora IL", -0.0147, -0.0772, 0.0479, 0
 "Denison IA", -0.0028, -0.0424, 0.0369, 0
 "Spencer IA", 0.0185, -0.0002, 0.0371, 0
 "Fort Dodge IA", 0.0041, -0.0243, 0.0325, 0
 "Rockford IL", 0.0079, -0.014, 0.0299, 0
 "Sioux Falls SD", 0.0201, -0.0009, 0.0412, 0
 "Charles City IA", 0.0197, -0.0075, 0.0469, 0
 "Hillsboro WI", 0.0245, -0.0005, 0.0494, 0
 "Stevens Point WI", -0.0013, -0.0241, 0.0215, 0
 "Iron Mountain MI", -0.0087, -0.0241, 0.0067, 0
 "Park Falls WI", -0.0037, -0.0198, 0.0123, 0
 "Ashland WI", -0.0037, -0.0248, 0.0173, 0
 "Hancock-Houghton AP MI", 0.0105, -0.0041, 0.025, 0
 "Oshkosh WI", -0.0037, -0.032, 0.0246, 0
 "Shawano WI", 0.0036, -0.0239, 0.0311, 0
 "Spooner WI", -0.0195, -0.0425, 0.0034, 0
 "Grundy Center IA", 0.0155, -0.0103, 0.0412, 0
 "Lansing IA", 0.0079, -0.0166, 0.0324, 0
 "Rhinelander WI", 0.0012, -0.0353, 0.0378, 0
 "Bergland Dam MI", -0.0065, -0.0241, 0.0111, 0
 "Alexandria", 0.0102, -0.0066, 0.0269, 0
 "Beardsley", 0.008, -0.0142, 0.0302, 0
 "Canby", -0.0023, -0.0184, 0.0138, 0
 "Crookston", 0.0023, -0.0167, 0.0214, 0
 "Duluth", -0.0021, -0.0277, 0.0235, 0
 "Fairmont", -0.0033, -0.0475, 0.0409, 0
 "Farmington", 0.002, -0.0199, 0.024, 0
 "Fergus_Falls", -0.0033, -0.0164, 0.0097, 0
 "Grand_Meadow", 0.0246, -0.0023, 0.0515, 0
 "Grand_Portage", 0.0067, -0.0085, 0.022, 0
 "Hinckley", 0.0188, -0.0118, 0.0493, 0
 "International_Falls", -0.0045, -0.0166, 0.0075, 0
 "Leech_Lake", -0.0009, -0.0129, 0.011, 0
 "Little_Falls", 0.0058, -0.0216, 0.0333, 0
 "Montevideo", -0.0017, -0.0289, 0.0255, 0
 "Moorhead", -0.0081, -0.0492, 0.033, 0
 "Morris", 0.0105, -0.0158, 0.0368, 0
 "Park_Rapids", -0.0214, -0.0597, 0.017, 0

"Pine_River_Dam",0.0089,-0.0073,0.0251,0
"Pipestone",0.0053,-0.0191,0.0298,0
"Pokegama_Dam",-0.0087,-0.0298,0.0125,0
"Red_Lake_Indian_Agency",-0.0084,-0.0465,0.0296,0
"Redwodd_Falls",0.0229,-0.0165,0.0623,0
"St_Cloud",-0.0044,-0.0263,0.0176,0
"St_Paul",-0.0162,-0.0321,-0.0003,1
"St_Peter",0.0175,-0.0246,0.0597,0
"St_Vincent",0.0055,-0.0332,0.0443,0
"Tower",0.0056,-0.0318,0.0431,0
"Warroad",0.005,-0.0193,0.0293,0
"Winnibigoshish",-0.0111,-0.0272,0.0049,0
"Winona",0.0199,-0.0035,0.0433,0
"Coastal",-0.0036,-0.2085,0.2013,0
"Inland",0.0871,0.0011,0.1731,1
"All",0.112,-0.2251,0.4491,0

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY", 0.0302, 0.0035, 0.057, 1
"Boston MA", -0.0223, -0.0699, 0.0252, 0
"Portland ME", 0.0017, -0.058, 0.0614, 0
"Gardiner ME", 0.0093, -0.0111, 0.0298, 0
"Albany NY", 0.0172, -0.0101, 0.0446, 0
"Concord NH", 0.0053, -0.0161, 0.0267, 0
"Montreal Q", 0.0098, -0.0103, 0.0299, 0
"Lakeport NH", 0.006, -0.0127, 0.0246, 0
"Burlington VT", 0.0033, -0.0064, 0.0129, 0
"Cornwall VT", 0.0018, -0.0136, 0.0171, 0
"Northfield VT", -0.003, -0.024, 0.018, 0
"Corinth VT", 0.002, -0.0118, 0.0158, 0
"Hanover NH", -0.0109, -0.0244, 0.0026, 0
"Rochester NY", 0.0077, -0.0052, 0.0207, 0
"Buffalo NY", -0.0035, -0.0232, 0.0162, 0
"Middletown CT", -0.0087, -0.039, 0.0216, 0
"Ithaca NY", -0.0069, -0.025, 0.0113, 0
"Amherst MA", 0.0124, -0.0208, 0.0456, 0
"Setauket Strong NY", 0.0228, -0.0056, 0.0513, 0
"Fitchburg MA", -0.0089, -0.037, 0.0193, 0
"Providence RI", -0.0055, -0.0293, 0.0183, 0
"Waterville ME", 0.0077, -0.0095, 0.0249, 0
"Lowville NY", 0.0172, -0.0085, 0.043, 0
"Cooperstown NY", 0.0315, -0.02, 0.0831, 0
"Berlin NH", -0.0098, -0.0323, 0.0128, 0
"Farmington ME", 0.0086, -0.0145, 0.0317, 0
"Eastport ME", 0.0285, -0.0001, 0.0572, 0
"Coastal", 0.0691, -0.0374, 0.1756, 0
"Inland", 0.0433, -0.0743, 0.161, 0
"All", 0.1112, -0.137, 0.3594, 0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Blaine"	0.0152	-0.003	0.0335	0
"Bellingham"	-0.0086	-0.0394	0.0221	0
"Quil"	0.0029	-0.0165	0.0223	0
"Clearwater"	0.0131	-0.0619	0.088	0
"Aberdeen"	0.0032	-0.0244	0.0307	0
"Raymond"	0.017	-0.0019	0.036	0
"Astoria"	0.0158	-0.0039	0.0354	0
"Tillamook"	0.0175	0.0025	0.0326	1
"Newport"	-0.0129	-0.0347	0.0089	0
"Florence"	-0.0095	-0.0328	0.0139	0
"North Bend"	-0.014	-0.0345	0.0064	0
"Bandon"	-0.0269	-0.0448	-0.009	1
"Port"	-0.0094	-0.0445	0.0258	0
"Crescent City"	0.0207	0.0015	0.0398	1
"Eureka"	-0.0129	-0.0485	0.0226	0
"Upper Mattole"	-0.0035	-0.0527	0.0457	0
"Fort Bragg"	0.0057	-0.0149	0.0262	0
"Ukiah"	0.0041	-0.0253	0.0334	0
"Healdsburg"	-0.0164	-0.0629	0.0301	0
"San Francisco"	0.006	-0.0232	0.0351	0
"Santa Cruz"	-0.0119	-0.0437	0.0199	0
"Big Sur"	0.0164	-0.0219	0.0547	0
"Paso Robles"	0.0113	-0.0067	0.0292	0
"Santa Maria"	0.0083	-0.0129	0.0294	0
"Santa Barbara"	0.0163	-0.0285	0.061	0
"Los Angeles"	0.0119	-0.011	0.0348	0
"Santa Ana"	-0.0048	-0.0238	0.0141	0
"Escondido"	0.0094	-0.0125	0.0312	0
"San Diego"	0.0064	-0.0104	0.0232	0
"Coastal"	-0.0636	-0.125	-0.0023	1
"Inland"	-0.0374	-0.1431	0.0682	0
"All"	-0.0993	-0.2509	0.0523	0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	0.0137	-0.0298	0.0572	0
"Galveston"	-0.0082	-0.0532	0.0369	0
"Shreveport"	-0.0177	-0.0478	0.0125	0
"Vicksburg"	-0.0099	-0.0442	0.0244	0
"New Orleans"	0.0014	-0.0372	0.04	0
"Memphis"	0.0036	-0.0234	0.0305	0
"Mobile"	0.0097	-0.0414	0.0607	0
"Nashville"	0.0155	-0.0051	0.036	0
"Montgomery"	-0.0155	-0.0388	0.0079	0
"Atlanta"	0.0063	-0.0161	0.0287	0
"Knoxville"	0.0152	-0.0003	0.0307	0
"Macon"	-0.0006	-0.0267	0.0256	0
"Quitman"	0.0108	-0.0287	0.0503	0
"Augusta"	0.0153	-0.0079	0.0385	0
"Key West"	-0.0428	-0.1429	0.0573	0
"Jacksonville"	0.0046	-0.0547	0.064	0
"Lenoir"	0.0256	0.0052	0.046	1
"Savannah"	0.0341	0.0035	0.0647	1
"Charleston"	0.0201	-0.021	0.0613	0
"Lynchburg"	0.0215	-0.0065	0.0494	0
"Wilmington"	0.0435	-0.0113	0.0983	0
"Weldon"	0.0254	-0.0316	0.0823	0
"Washington"	0.0309	0.0083	0.0535	1
"Norfolk"	0.0389	-0.0199	0.0977	0
"Coastal"	0.0314	-0.0666	0.1295	0
"Inland"	0.0022	-0.0707	0.0751	0
"All"	0.0193	-0.0487	0.0873	0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	-0.0077	-0.0172	0.0019	0
"Galveston"	-0.0015	-0.0164	0.0134	0
"Shreveport"	0.014	-0.0033	0.0312	0
"Vicksburg"	0.0064	-0.0055	0.0184	0
"New Orleans"	0.0112	0.004	0.0185	1
"Memphis"	0.0092	-0.0038	0.0221	0
"Mobile"	0.0066	0.0005	0.0128	1
"Nashville"	0.0055	-0.0034	0.0145	0
"Montgomery"	0.0065	0.0002	0.0128	1
"Atlanta"	0.0036	-0.0055	0.0128	0
"Knoxville"	-0.0002	-0.0188	0.0184	0
"Macon"	-0.0086	-0.0314	0.0143	0
"Quitman"	0.0004	-0.0179	0.0186	0
"Augusta"	0.001	-0.0122	0.0142	0
"Key West"	0.0049	0.0003	0.0095	1
"Jacksonville"	0.0055	-0.0069	0.0179	0
"Lenoir"	-0.0129	-0.0387	0.0129	0
"Savannah"	-0.0015	-0.0149	0.012	0
"Charleston"	-0.0023	-0.0248	0.0201	0
"Lynchburg"	0.0052	-0.0102	0.0207	0
"Wilmington"	0.0168	0.0004	0.0332	1
"Weldon"	0.0058	-0.0234	0.035	0
"Washington"	-0.0033	-0.0148	0.0082	0
"Norfolk"	0.0079	-0.0104	0.0261	0
"Coastal"	0.0252	-0.0711	0.1216	0
"Inland"	0.035	-0.0709	0.1408	0
"All"	0.0267	-0.0589	0.1124	0

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY", 0.0133, -0.008, 0.0345, 0
"Boston MA", 0.0118, 0.0017, 0.0219, 1
"Portland ME", 0.0153, 0.0057, 0.0248, 1
"Gardiner ME", 0.0136, -0.0009, 0.0281, 0
"Albany NY", 0.0132, -0.0001, 0.0266, 0
"Concord NH", 0.0121, -0.0041, 0.0283, 0
"Montreal Q", 0.0078, -0.0185, 0.0341, 0
"Lakeport NH", 0.0019, -0.0183, 0.0221, 0
"Burlington VT", 0.0116, -0.0063, 0.0294, 0
"Cornwall VT", 0.0112, -0.0021, 0.0245, 0
"Northfield VT", 0.0237, 0.0129, 0.0345, 1
"Corinth VT", 0.0149, -0.0002, 0.0299, 0
"Hanover NH", 0.0096, -0.0046, 0.0237, 0
"Rochester NY", 0.011, 0.0021, 0.0199, 1
"Buffalo NY", 0.0148, -0.0008, 0.0304, 0
"Middletown CT", 0.0051, -0.0159, 0.026, 0
"Ithaca NY", 0.0058, -0.0018, 0.0134, 0
"Amherst MA", 0.0124, -0.0004, 0.0253, 0
"Setauket Strong NY", 0.0093, -0.0054, 0.0241, 0
"Fitchburg MA", 0.0099, -0.0056, 0.0254, 0
"Providence RI", 0.004, -0.0191, 0.0272, 0
"Waterville ME", 0.0041, -0.0179, 0.0261, 0
"Lowville NY", 0.0127, -0.0033, 0.0286, 0
"Cooperstown NY", 0.0087, -0.0189, 0.0364, 0
"Berlin NH", 0.0116, -0.013, 0.0363, 0
"Farmington ME", 0.0134, -0.0019, 0.0286, 0
"Eastport ME", 0.0428, 0.0294, 0.0562, 1
"Coastal", 0.1334, 0.0482, 0.2186, 1
"Inland", 0.1513, 0.03, 0.2727, 1
"All", 0.2019, 0.1233, 0.2806, 1

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.0245, 0.0098, 0.0391, 1
 "Milwaukee WI", 0.0151, 0.0047, 0.0255, 1
 "Green Bay WI", 0.0099, -0.0107, 0.0305, 0
 "Chippewa Falls WI", -0.0051, -0.0203, 0.0102, 0
 "Medford WI", -0.0066, -0.0256, 0.0125, 0
 "Dubuque IA", 0.016, -0.0038, 0.0358, 0
 "Des Moines IA", 0.0109, 0.0015, 0.0203, 1
 "Cedar Rapids IA", 0.011, 0.0015, 0.0206, 1
 "Davenport IA", 0.0187, 0.0065, 0.0308, 1
 "Sioux City IA", 0.0079, -0.0115, 0.0274, 0
 "Aurora IL", 0.0091, -0.0048, 0.023, 0
 "Denison IA", 0.0045, -0.0041, 0.0131, 0
 "Spencer IA", 0.0086, -0.0086, 0.0257, 0
 "Fort Dodge IA", 0.004, -0.0118, 0.0198, 0
 "Rockford IL", 0.0151, -0.0007, 0.031, 0
 "Sioux Falls SD", -0.0047, -0.0216, 0.0123, 0
 "Charles City IA", 0.0157, 0.002, 0.0294, 1
 "Hillsboro WI", 0.0121, -0.0036, 0.0279, 0
 "Stevens Point WI", -0.0047, -0.019, 0.0095, 0
 "Iron Mountain MI", -0.0004, -0.0121, 0.0113, 0
 "Park Falls WI", -0.0058, -0.0135, 0.0019, 0
 "Ashland WI", -0.0028, -0.0132, 0.0077, 0
 "Hancock-Houghton AP MI", -0.0021, -0.0122, 0.008, 0
 "Oshkosh WI", 0.0106, -0.0114, 0.0325, 0
 "Shawano WI", 0.0045, -0.0042, 0.0132, 0
 "Spooner WI", 0.0016, -0.0155, 0.0188, 0
 "Grundy Center IA", 0.0046, -0.0102, 0.0194, 0
 "Lansing IA", 0.0152, -0.0009, 0.0313, 0
 "Rhinelander WI", -0.0015, -0.009, 0.006, 0
 "Bergland Dam MI", 0.0043, -0.0076, 0.0162, 0
 "Alexandria", 0.005, -0.0051, 0.0151, 0
 "Beardsley", 0.0049, -0.016, 0.0259, 0
 "Canby", -0.0013, -0.0131, 0.0105, 0
 "Crookston", 0.0067, -0.0039, 0.0173, 0
 "Duluth", 0.0138, 0.0013, 0.0262, 1
 "Fairmont", 0.0034, -0.0087, 0.0155, 0
 "Farmington", 0.0157, 0.0005, 0.0309, 1
 "Fergus_Falls", 0.0132, -0.0005, 0.0269, 0
 "Grand_Meadow", 0.0075, -0.0143, 0.0292, 0
 "Grand_Portage", 0.0095, -0.0046, 0.0237, 0
 "Hinckley", 0.0048, -0.0109, 0.0205, 0
 "International_Falls", 0.0009, -0.0109, 0.0126, 0
 "Leech_Lake", -0.0019, -0.0145, 0.0107, 0
 "Little_Falls", 0.0069, -0.0055, 0.0193, 0
 "Montevideo", 0.0129, 0.0035, 0.0224, 1
 "Moorhead", 0.0085, -0.0246, 0.0416, 0
 "Morris", 0.0092, 0.0028, 0.0155, 1
 "Park_Rapids", -0.0005, -0.0163, 0.0152, 0

"Pine_River_Dam",-0.0039,-0.0171,0.0093,0
"Pipestone",0.005,-0.0041,0.014,0
"Pokegama_Dam",0.0003,-0.0203,0.0209,0
"Red_Lake_Indian_Agency",-0.0094,-0.0302,0.0114,0
"Redwodd_Falls",0.0134,-0.0027,0.0295,0
"St_Cloud",0.0025,-0.021,0.0261,0
"St_Paul",0.0094,-0.0044,0.0233,0
"St_Peter",0.0097,-0.0042,0.0235,0
"St_Vincent",0,-0.0169,0.0169,0
"Tower",0.0024,-0.0052,0.01,0
"Warroad",0.0041,-0.0135,0.0218,0
"Winnibigoshish",-0.0049,-0.0214,0.0116,0
"Winona",0.0097,-0.0054,0.0249,0
"Coastal",0.091,-0.0682,0.2501,0
"Inland",0.1547,0.0753,0.2341,1
"All",0.1212,-0.0299,0.2723,0

"", "Trend", "CI-lower", "CI-upper", "Sig"
"Blaine",-0.0094,-0.0237,0.0049,0
"Bellingham",0.0029,-0.0104,0.0162,0
"Quil",0.0017,-0.0183,0.0218,0
"Clearwater",-0.0082,-0.0264,0.01,0
"Aberdeen",0.0213,0.0005,0.0421,1
"Raymond",0.0045,-0.0154,0.0243,0
"Astoria",-0.0098,-0.0277,0.0081,0
"Tillamook",-0.0086,-0.0245,0.0073,0
"Newport",-0.0135,-0.0303,0.0033,0
"Florence",-0.0018,-0.0101,0.0065,0
"North Bend",0.0073,-0.0004,0.015,0
"Bandon",0.0014,-0.0111,0.014,0
"Port",-0.0045,-0.026,0.017,0
"Crescent City",-0.0121,-0.0291,0.0048,0
"Eureka",-0.009,-0.0256,0.0076,0
"Upper Mattole",-0.0046,-0.014,0.0048,0
"Fort Bragg",-0.0025,-0.0158,0.0109,0
"Ukiah",0.0049,-0.0088,0.0187,0
"Healdsburg",0.0009,-0.0184,0.0202,0
"San Francisco",0.0065,-0.0042,0.0171,0
"Santa Cruz",0.0085,-0.0023,0.0193,0
"Big Sur",0.0045,-0.0081,0.0171,0
"Paso Robles",-0.0027,-0.0174,0.0119,0
"Santa Maria",0.0042,-0.0107,0.0192,0
"Santa Barbara",0.004,-0.0073,0.0152,0
"Los Angeles",0.005,-0.0057,0.0156,0
"Santa Ana",0.0028,-0.0104,0.0159,0
"Escondido",-0.0054,-0.019,0.0083,0
"San Diego",0.0054,-0.0078,0.0186,0
"Coastal",-0.0238,-0.1269,0.0794,0
"Inland",-0.0283,-0.1292,0.0726,0
"All",-0.0212,-0.1138,0.0713,0

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.0301, 0.0058, 0.0544, 1
 "Milwaukee WI", 0.012, -0.0113, 0.0353, 0
 "Green Bay WI", 0.0386, 0.0273, 0.05, 1
 "Chippewa Falls WI", 0.0099, -0.02, 0.0399, 0
 "Medford WI", 0.003, -0.0171, 0.0232, 0
 "Dubuque IA", 0.0048, -0.0468, 0.0563, 0
 "Des Moines IA", 0.0207, 0.003, 0.0383, 1
 "Cedar Rapids IA", 0.0036, -0.0134, 0.0206, 0
 "Davenport IA", 0.0284, 0.0126, 0.0442, 1
 "Sioux City IA", 0.0335, 0.011, 0.056, 1
 "Aurora IL", 0.0174, 0.0009, 0.034, 1
 "Denison IA", -0.0013, -0.032, 0.0295, 0
 "Spencer IA", 0.0317, 0.005, 0.0584, 1
 "Fort Dodge IA", 0.0078, -0.0233, 0.0389, 0
 "Rockford IL", 0, -0.0212, 0.0213, 0
 "Sioux Falls SD", 0.0153, -0.0159, 0.0466, 0
 "Charles City IA", 0.0314, 0.0094, 0.0535, 1
 "Hillsboro WI", 0.0348, 0.0182, 0.0515, 1
 "Stevens Point WI", 0.0156, -0.0095, 0.0407, 0
 "Iron Mountain MI", 0.0034, -0.0334, 0.0403, 0
 "Park Falls WI", -0.0085, -0.0378, 0.0209, 0
 "Ashland WI", -0.0142, -0.0471, 0.0186, 0
 "Hancock-Houghton AP MI", -0.0123, -0.0538, 0.0292, 0
 "Oshkosh WI", 0.0338, 0.0088, 0.0587, 1
 "Shawano WI", 0.0167, -0.016, 0.0494, 0
 "Spooner WI", -0.0027, -0.0304, 0.0249, 0
 "Grundy Center IA", 0.0221, 0.0011, 0.0432, 1
 "Lansing IA", 0.0274, 0.0029, 0.0518, 1
 "Rhineland WI", 0.0056, -0.0147, 0.0259, 0
 "Bergland Dam MI", -0.0053, -0.031, 0.0205, 0
 "Alexandria", 0.0138, -0.0018, 0.0294, 0
 "Beardsley", 0.0173, -0.0113, 0.0459, 0
 "Canby", 0.011, -0.0055, 0.0275, 0
 "Crookston", 0.0116, -0.0114, 0.0346, 0
 "Duluth", -0.0143, -0.0336, 0.005, 0
 "Fairmont", 0.007, -0.0257, 0.0396, 0
 "Farmington", 0.0232, -0.0087, 0.0551, 0
 "Fergus_Falls", 0.0253, -0.0082, 0.0588, 0
 "Grand_Meadow", 0.0302, 0.0135, 0.0469, 1
 "Grand_Portage", 0.0278, 0.0099, 0.0458, 1
 "Hinckley", 0.0005, -0.0269, 0.0279, 0
 "International_Falls", 0.0183, -0.001, 0.0377, 0
 "Leech_Lake", -0.0039, -0.0296, 0.0217, 0
 "Little_Falls", 0.0008, -0.0386, 0.0402, 0
 "Montevideo", 0.0074, -0.0207, 0.0356, 0
 "Moorhead", 0.0254, -0.0206, 0.0715, 0
 "Morris", 0.01, -0.0057, 0.0258, 0
 "Park_Rapids", -0.0187, -0.0491, 0.0118, 0

"Pine_River_Dam",-0.0077,-0.024,0.0085,0
"Pipestone",0.013,-0.0057,0.0318,0
"Pokegama_Dam",0.0051,-0.0377,0.048,0
"Red_Lake_Indian_Agency",0.0181,-0.0164,0.0525,0
"Redwodd_Falls",0.0236,0.0055,0.0416,1
"St_Cloud",0.0109,-0.03,0.0518,0
"St_Paul",0.0067,-0.0281,0.0415,0
"St_Peter",0.0286,0.0031,0.054,1
"St_Vincent",0.0195,0.0013,0.0378,1
"Tower",0.0038,-0.0147,0.0223,0
"Warroad",0.0283,0.0039,0.0528,1
"Winnibigoshish",-0.0087,-0.0358,0.0184,0
"Winona",0.0296,0.0166,0.0426,1
"Coastal",0.2607,0.1505,0.3709,1
"Inland",0.2574,0.0805,0.4344,1
"All",0.3316,0.0884,0.5748,1

"", "Trend", "CI-lower", "CI-upper", "Sig"
"NYC Central Park NY", 0.0297, -0.017, 0.0765, 0
"Boston MA", -0.0045, -0.0347, 0.0256, 0
"Portland ME", 0.026, -0.0029, 0.055, 0
"Gardiner ME", 0.0218, -0.0019, 0.0455, 0
"Albany NY", 0.025, 0.0019, 0.048, 1
"Concord NH", 0.0339, 0.0063, 0.0614, 1
"Montreal Q", 0.0414, 0.0062, 0.0766, 1
"Lakeport NH", 0.0318, -0.0014, 0.0651, 0
"Burlington VT", 0.0292, 0.0044, 0.054, 1
"Cornwall VT", 0.0301, 0.0069, 0.0534, 1
"Northfield VT", 0.0308, 0.0049, 0.0568, 1
"Corinth VT", 0.0374, 0.018, 0.0569, 1
"Hanover NH", 0.0212, -0.0041, 0.0465, 0
"Rochester NY", 0.0243, 0.003, 0.0457, 1
"Buffalo NY", 0.0157, -0.0097, 0.0411, 0
"Middletown CT", -0.0077, -0.0608, 0.0455, 0
"Ithaca NY", 0.0122, -0.0054, 0.0298, 0
"Amherst MA", 0.017, -0.0142, 0.0482, 0
"Setauket Strong NY", 0.0201, 0.0042, 0.036, 1
"Fitchburg MA", -0.0077, -0.0382, 0.0228, 0
"Providence RI", 0.0098, -0.0094, 0.0291, 0
"Waterville ME", 0.0203, -0.004, 0.0446, 0
"Lowville NY", 0.0195, -0.0074, 0.0464, 0
"Cooperstown NY", 0.0485, 0.0213, 0.0757, 1
"Berlin NH", 0.0366, 0.0164, 0.0568, 1
"Farmington ME", 0.0292, 0, 0.0585, 0
"Eastport ME", 0.0356, 0.0024, 0.0689, 1
"Coastal", 0.1923, 0.0638, 0.3208, 1
"Inland", 0.2931, 0.1272, 0.459, 1
"All", 0.2928, 0.1158, 0.4698, 1

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Blaine", 0.0099, -0.0096, 0.0293, 0
 "Bellingham", 0.0032, -0.0464, 0.0527, 0
 "Quil", 0.0323, 0.0104, 0.0541, 1
 "Clearwater", 0.0004, -0.0645, 0.0653, 0
 "Aberdeen", 0.045, 0.005, 0.0849, 1
 "Raymond", 0.0239, -0.0108, 0.0585, 0
 "Astoria", 0.0091, -0.0362, 0.0543, 0
 "Tillamook", 0.0127, -0.0095, 0.0348, 0
 "Newport", -0.0339, -0.0745, 0.0067, 0
 "Florence", -0.0079, -0.0304, 0.0146, 0
 "North Bend", 0.0122, -0.0136, 0.038, 0
 "Bandon", -0.0135, -0.0333, 0.0063, 0
 "Port", -0.0298, -0.0478, -0.0117, 1
 "Crescent City", -0.0073, -0.0494, 0.0348, 0
 "Eureka", -0.0095, -0.0368, 0.0178, 0
 "Upper Mattole", -0.0032, -0.0307, 0.0243, 0
 "Fort Bragg", -0.011, -0.0376, 0.0156, 0
 "Ukiah", -0.0096, -0.0318, 0.0126, 0
 "Healdsburg", -0.0236, -0.05, 0.0028, 0
 "San Francisco", 0.0043, -0.0288, 0.0373, 0
 "Santa Cruz", 0.0029, -0.0263, 0.0322, 0
 "Big Sur", -0.0102, -0.0332, 0.0127, 0
 "Paso Robles", 0.0138, -0.0128, 0.0403, 0
 "Santa Maria", 0.0087, -0.0181, 0.0354, 0
 "Santa Barbara", 0.0075, -0.0153, 0.0303, 0
 "Los Angeles", 0.0076, -0.0302, 0.0454, 0
 "Santa Ana", 0.0009, -0.0385, 0.0402, 0
 "Escondido", 0.0089, -0.0276, 0.0453, 0
 "San Diego", 0.0143, -0.0099, 0.0384, 0
 "Coastal", -0.0213, -0.1619, 0.1194, 0
 "Inland", -0.0643, -0.2203, 0.0916, 0
 "All", -0.038, -0.1769, 0.101, 0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	0.0078	-0.0195	0.035	0
"Galveston"	0.0281	0.0014	0.0548	1
"Shreveport"	0.0328	-0.0051	0.0708	0
"Vicksburg"	0.0123	-0.0336	0.0582	0
"New Orleans"	0.0207	-0.0012	0.0426	0
"Memphis"	0.0057	-0.0141	0.0254	0
"Mobile"	0.0123	-0.0095	0.0341	0
"Nashville"	0.0018	-0.0237	0.0273	0
"Montgomery"	0.0103	-0.026	0.0466	0
"Atlanta"	0.0153	-0.0115	0.0421	0
"Knoxville"	0.0199	-0.0052	0.0451	0
"Macon"	0.0181	-0.0068	0.043	0
"Quitman"	0.0238	0.0019	0.0458	1
"Augusta"	0.0223	-0.0047	0.0493	0
"Key West"	0.0113	-0.0113	0.0339	0
"Jacksonville"	0.0093	-0.015	0.0335	0
"Lenoir"	0.0166	-0.0169	0.05	0
"Savannah"	-0.0033	-0.0294	0.0228	0
"Charleston"	0.0074	-0.0246	0.0395	0
"Lynchburg"	0.0278	0.0018	0.0538	1
"Wilmington"	0.0183	-0.0028	0.0395	0
"Weldon"	0.0364	0.009	0.0637	1
"Washington"	0.0153	-0.015	0.0457	0
"Norfolk"	0.012	-0.0122	0.0363	0
"Coastal"	0.0469	-0.1134	0.2071	0
"Inland"	0.1926	0.0006	0.3847	1
"All"	0.094	-0.078	0.266	0

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "Madison WI", 0.0463, 0.0123, 0.0803, 1
 "Milwaukee WI", 0.0023, -0.0532, 0.0579, 0
 "Green Bay WI", 0.0197, -0.016, 0.0555, 0
 "Chippewa Falls WI", 0.0098, -0.0635, 0.0831, 0
 "Medford WI", -0.0025, -0.062, 0.0569, 0
 "Dubuque IA", 0.0711, 0.0173, 0.125, 1
 "Des Moines IA", 0.0089, -0.059, 0.0769, 0
 "Cedar Rapids IA", 0.0093, -0.0216, 0.0402, 0
 "Davenport IA", 0.0178, -0.0315, 0.0671, 0
 "Sioux City IA", 0.03, -0.0266, 0.0867, 0
 "Aurora IL", 0.01, -0.0396, 0.0596, 0
 "Denison IA", 0.0032, -0.0769, 0.0834, 0
 "Spencer IA", 0.0267, -0.0458, 0.0992, 0
 "Fort Dodge IA", -0.0117, -0.0604, 0.037, 0
 "Rockford IL", -0.0072, -0.0444, 0.03, 0
 "Sioux Falls SD", 0.0397, -0.0073, 0.0866, 0
 "Charles City IA", 0.0596, 0.0132, 0.106, 1
 "Hillsboro WI", 0.0382, -0.0026, 0.079, 0
 "Stevens Point WI", 0.0273, -0.0361, 0.0906, 0
 "Iron Mountain MI", 0.0358, -0.0434, 0.115, 0
 "Park Falls WI", 0.0111, -0.0423, 0.0646, 0
 "Ashland WI", 0.009, -0.0473, 0.0653, 0
 "Hancock-Houghton AP MI", -0.0096, -0.0916, 0.0724, 0
 "Oshkosh WI", 0.0291, -0.0644, 0.1226, 0
 "Shawano WI", 0.0168, -0.0714, 0.1051, 0
 "Spooner WI", -0.0195, -0.0787, 0.0398, 0
 "Grundy Center IA", 0.0217, -0.0453, 0.0887, 0
 "Lansing IA", 0.0169, -0.0354, 0.0692, 0
 "Rhinelander WI", 0.0063, -0.0397, 0.0524, 0
 "Bergland Dam MI", -0.0001, -0.0423, 0.0421, 0
 "Alexandria", 0.0047, -0.0428, 0.0521, 0
 "Beardsley", 0.0288, -0.0225, 0.08, 0
 "Canby", 0.0194, -0.0181, 0.0568, 0
 "Crookston", 0.0008, -0.0677, 0.0694, 0
 "Duluth", -0.0131, -0.0547, 0.0285, 0
 "Fairmont", -0.0183, -0.068, 0.0315, 0
 "Farmington", 0.0387, -0.0148, 0.0922, 0
 "Fergus_Falls", 0.0349, -0.0242, 0.094, 0
 "Grand_Meadow", 0.0202, -0.0091, 0.0496, 0
 "Grand_Portage", 0.0279, -0.0234, 0.0792, 0
 "Hinckley", 0, -0.0785, 0.0785, 0
 "International_Falls", 0.0401, 0.0088, 0.0714, 1
 "Leech_Lake", -0.0442, -0.0811, -0.0073, 1
 "Little_Falls", 0.037, -0.0287, 0.1027, 0
 "Montevideo", 0.0128, -0.0484, 0.0739, 0
 "Moorhead", -0.0006, -0.1128, 0.1115, 0
 "Morris", 0.0066, -0.0258, 0.0391, 0
 "Park_Rapids", -0.0553, -0.1034, -0.0073, 1

"Pine_River_Dam",0.0047,-0.0297,0.039,0
"Pipestone",0.0055,-0.0466,0.0575,0
"Pokegama_Dam",-0.0511,-0.0918,-0.0104,1
"Red_Lake_Indian_Agency",-0.0141,-0.0871,0.0589,0
"Redwodd_Falls",0.0201,-0.0193,0.0594,0
"St_Cloud",0.0517,-0.0163,0.1198,0
"St_Paul",-0.0261,-0.0644,0.0123,0
"St_Peter",0.0216,-0.0337,0.077,0
"St_Vincent",0.0136,-0.0409,0.0681,0
"Tower",0.0034,-0.0384,0.0452,0
"Warroad",-0.0014,-0.0369,0.034,0
"Winnibigoshish",-0.0351,-0.0786,0.0084,0
"Winona",0.0404,0.0074,0.0733,1
"Coastal",0.1952,-0.0505,0.4409,0
"Inland",0.0006,-0.345,0.3463,0
"All",-0.0132,-0.3581,0.3316,0

"", "Trend", "CI-lower", "CI-upper", "Sig"
 "NYC Central Park NY", -0.0197, -0.0811, 0.0417, 0
 "Boston MA", 0.0066, -0.0443, 0.0575, 0
 "Portland ME", 0.0535, -0.0094, 0.1164, 0
 "Gardiner ME", 0.024, -0.0313, 0.0793, 0
 "Albany NY", 0.0399, -0.0265, 0.1063, 0
 "Concord NH", 0.0349, -0.0424, 0.1121, 0
 "Montreal Q", 0.0348, -0.0289, 0.0984, 0
 "Lakeport NH", 0.0612, 0.0216, 0.1009, 1
 "Burlington VT", 0.0107, -0.0296, 0.051, 0
 "Cornwall VT", 0.0268, -0.0216, 0.0752, 0
 "Northfield VT", 0.01, -0.0314, 0.0514, 0
 "Corinth VT", 0.0273, -0.0227, 0.0772, 0
 "Hanover NH", 0.0007, -0.0686, 0.0701, 0
 "Rochester NY", 0.054, -0.0153, 0.1232, 0
 "Buffalo NY", 0.0135, -0.0285, 0.0554, 0
 "Middletown CT", -0.0559, -0.1057, -0.0061, 1
 "Ithaca NY", 0.0123, -0.0345, 0.059, 0
 "Amherst MA", -0.0158, -0.0735, 0.0419, 0
 "Setauket Strong NY", 0.0195, -0.0284, 0.0674, 0
 "Fitchburg MA", -0.0402, -0.0815, 0.0011, 0
 "Providence RI", 0.0322, -0.0142, 0.0786, 0
 "Waterville ME", 0.0362, -0.0312, 0.1035, 0
 "Lowville NY", 0.0474, -0.0194, 0.1143, 0
 "Cooperstown NY", 0.0656, -0.0322, 0.1634, 0
 "Berlin NH", 0.0295, -0.0192, 0.0783, 0
 "Farmington ME", 0.0492, -0.0158, 0.1142, 0
 "Eastport ME", 0.0673, -0.0335, 0.1681, 0
 "Coastal", 0.236, -0.0361, 0.5081, 0
 "Inland", 0.448, 0.1853, 0.7107, 1
 "All", 0.4985, 0.211, 0.786, 1

"", "Trend", "CI-lower", "CI-upper", "Sig"
"Blaine",-0.0011,-0.0661,0.064,0
"Bellingham",-0.0283,-0.1354,0.0788,0
"Quil",0.0353,-0.0123,0.0829,0
"Clearwater",0.0638,-0.065,0.1925,0
"Aberdeen",-0.0118,-0.0629,0.0392,0
"Raymond",0.0042,-0.0782,0.0865,0
"Astoria",0.0258,-0.0389,0.0905,0
"Tillamook",0.0167,-0.0516,0.085,0
"Newport",-0.0658,-0.173,0.0413,0
"Florence",-0.0111,-0.0791,0.0569,0
"North Bend",-0.0333,-0.0761,0.0095,0
"Bandon",-0.0089,-0.0689,0.0512,0
"Port",-0.0541,-0.1182,0.01,0
"Crescent City",0.0357,-0.0401,0.1115,0
"Eureka",-0.0067,-0.069,0.0556,0
"Upper Mattole",-0.0181,-0.0897,0.0535,0
"Fort Bragg",-0.0004,-0.0676,0.0667,0
"Ukiah",-0.0255,-0.0884,0.0374,0
"Healdsburg",-0.0274,-0.0956,0.0407,0
"San Francisco",-0.027,-0.09,0.036,0
"Santa Cruz",-0.003,-0.082,0.0761,0
"Big Sur",-0.014,-0.0882,0.0601,0
"Paso Robles",0.0226,-0.0597,0.105,0
"Santa Maria",0.0061,-0.0782,0.0903,0
"Santa Barbara",0.0183,-0.0619,0.0984,0
"Los Angeles",0.0122,-0.0736,0.098,0
"Santa Ana",-0.0149,-0.1046,0.0747,0
"Escondido",-0.0009,-0.0596,0.0577,0
"San Diego",0.0018,-0.0531,0.0566,0
"Coastal",-0.0185,-0.4903,0.4532,0
"Inland",-0.1352,-0.627,0.3565,0
"All",0.003,-0.435,0.4409,0

	"Trend"	"CI-lower"	"CI-upper"	"Sig"
"Austin"	0.0283	-0.0271	0.0838	0
"Galveston"	0.0555	-0.0161	0.127	0
"Shreveport"	0.0062	-0.0728	0.0852	0
"Vicksburg"	-0.0294	-0.0869	0.0281	0
"New Orleans"	-0.017	-0.0599	0.0259	0
"Memphis"	-0.0063	-0.042	0.0294	0
"Mobile"	-0.0045	-0.052	0.0431	0
"Nashville"	0.0005	-0.0554	0.0564	0
"Montgomery"	-0.0033	-0.0828	0.0762	0
"Atlanta"	0.0428	-0.0253	0.111	0
"Knoxville"	0.0509	0.0168	0.0849	1
"Macon"	0.0347	-0.0056	0.0749	0
"Quitman"	0.0171	-0.0237	0.058	0
"Augusta"	0.0224	-0.0468	0.0916	0
"Key West"	0.0058	-0.0432	0.0548	0
"Jacksonville"	0.02	-0.0469	0.087	0
"Lenoir"	0.0381	-0.0347	0.1108	0
"Savannah"	-0.0013	-0.0844	0.0818	0
"Charleston"	0.0465	0.0119	0.0811	1
"Lynchburg"	0.0402	-0.0115	0.0918	0
"Wilmington"	0.0224	-0.0451	0.0899	0
"Weldon"	0.063	0.0297	0.0963	1
"Washington"	0.0613	0.0161	0.1064	1
"Norfolk"	0.0357	-0.016	0.0874	0
"Coastal"	-0.0004	-0.4138	0.413	0
"Inland"	0.4212	-0.0227	0.8652	0
"All"	0.3273	-0.1496	0.8041	0

1958	3	1958.2027	315.71	314.44	-1	-9.99	-0.99
1958	4	1958.2877	317.45	315.16	-1	-9.99	-0.99
1958	5	1958.3699	317.51	314.69	-1	-9.99	-0.99
1958	6	1958.4548	317.27	315.15	-1	-9.99	-0.99
1958	7	1958.5370	315.87	315.20	-1	-9.99	-0.99
1958	8	1958.6219	314.93	316.21	-1	-9.99	-0.99
1958	9	1958.7068	313.21	316.11	-1	-9.99	-0.99
1958	10	1958.7890	312.42	315.41	-1	-9.99	-0.99
1958	11	1958.8740	313.33	315.21	-1	-9.99	-0.99
1958	12	1958.9562	314.67	315.43	-1	-9.99	-0.99
1959	1	1959.0411	315.58	315.52	-1	-9.99	-0.99
1959	2	1959.1260	316.49	315.84	-1	-9.99	-0.99
1959	3	1959.2027	316.65	315.37	-1	-9.99	-0.99
1959	4	1959.2877	317.72	315.42	-1	-9.99	-0.99
1959	5	1959.3699	318.29	315.46	-1	-9.99	-0.99
1959	6	1959.4548	318.15	316.00	-1	-9.99	-0.99
1959	7	1959.5370	316.54	315.87	-1	-9.99	-0.99
1959	8	1959.6219	314.80	316.09	-1	-9.99	-0.99
1959	9	1959.7068	313.84	316.75	-1	-9.99	-0.99
1959	10	1959.7890	313.33	316.34	-1	-9.99	-0.99
1959	11	1959.8740	314.81	316.69	-1	-9.99	-0.99
1959	12	1959.9562	315.58	316.35	-1	-9.99	-0.99
1960	1	1960.0410	316.43	316.38	-1	-9.99	-0.99
1960	2	1960.1257	316.98	316.33	-1	-9.99	-0.99
1960	3	1960.2049	317.58	316.27	-1	-9.99	-0.99
1960	4	1960.2896	319.03	316.70	-1	-9.99	-0.99
1960	5	1960.3716	320.03	317.19	-1	-9.99	-0.99
1960	6	1960.4563	319.58	317.45	-1	-9.99	-0.99
1960	7	1960.5383	318.18	317.54	-1	-9.99	-0.99
1960	8	1960.6230	315.90	317.22	-1	-9.99	-0.99
1960	9	1960.7077	314.17	317.10	-1	-9.99	-0.99
1960	10	1960.7896	313.83	316.85	-1	-9.99	-0.99
1960	11	1960.8743	315.00	316.89	-1	-9.99	-0.99
1960	12	1960.9563	316.19	316.96	-1	-9.99	-0.99
1961	1	1961.0411	316.89	316.84	-1	-9.99	-0.99
1961	2	1961.1260	317.70	317.05	-1	-9.99	-0.99
1961	3	1961.2027	318.54	317.25	-1	-9.99	-0.99
1961	4	1961.2877	319.48	317.16	-1	-9.99	-0.99
1961	5	1961.3699	320.58	317.73	-1	-9.99	-0.99
1961	6	1961.4548	319.77	317.61	-1	-9.99	-0.99
1961	7	1961.5370	318.56	317.89	-1	-9.99	-0.99
1961	8	1961.6219	316.79	318.09	-1	-9.99	-0.99
1961	9	1961.7068	314.99	317.92	-1	-9.99	-0.99
1961	10	1961.7890	315.31	318.34	-1	-9.99	-0.99
1961	11	1961.8740	316.10	318.00	-1	-9.99	-0.99
1961	12	1961.9562	317.01	317.78	-1	-9.99	-0.99
1962	1	1962.0411	317.94	317.89	-1	-9.99	-0.99
1962	2	1962.1260	318.55	317.89	-1	-9.99	-0.99
1962	3	1962.2027	319.68	318.39	-1	-9.99	-0.99

1962	4	1962.2877	320.57	318.24	-1	-9.99	-0.99
1962	5	1962.3699	321.02	318.16	-1	-9.99	-0.99
1962	6	1962.4548	320.62	318.45	-1	-9.99	-0.99
1962	7	1962.5370	319.61	318.94	-1	-9.99	-0.99
1962	8	1962.6219	317.40	318.71	-1	-9.99	-0.99
1962	9	1962.7068	316.24	319.18	-1	-9.99	-0.99
1962	10	1962.7890	315.42	318.46	-1	-9.99	-0.99
1962	11	1962.8740	316.69	318.59	-1	-9.99	-0.99
1962	12	1962.9562	317.70	318.47	-1	-9.99	-0.99
1963	1	1963.0411	318.74	318.69	-1	-9.99	-0.99
1963	2	1963.1260	319.07	318.41	-1	-9.99	-0.99
1963	3	1963.2027	319.86	318.57	-1	-9.99	-0.99
1963	4	1963.2877	321.38	319.05	-1	-9.99	-0.99
1963	5	1963.3699	322.24	319.38	-1	-9.99	-0.99
1963	6	1963.4548	321.49	319.31	-1	-9.99	-0.99
1963	7	1963.5370	319.74	319.07	-1	-9.99	-0.99
1963	8	1963.6219	317.77	319.07	-1	-9.99	-0.99
1963	9	1963.7068	316.21	319.16	-1	-9.99	-0.99
1963	10	1963.7890	315.99	319.03	-1	-9.99	-0.99
1963	11	1963.8740	317.07	318.98	-1	-9.99	-0.99
1963	12	1963.9562	318.35	319.13	-1	-9.99	-0.99
1964	1	1964.0410	319.57	319.52	-1	-9.99	-0.99
1964	2	1964.1257	320.04	319.37	-1	-9.99	-0.99
1964	3	1964.2049	320.75	319.41	-1	-9.99	-0.99
1964	4	1964.2896	321.84	319.46	-1	-9.99	-0.99
1964	5	1964.3716	322.25	319.37	-1	-9.99	-0.99
1964	6	1964.4563	321.89	319.73	-1	-9.99	-0.99
1964	7	1964.5383	320.44	319.79	-1	-9.99	-0.99
1964	8	1964.6230	318.69	320.03	-1	-9.99	-0.99
1964	9	1964.7077	316.71	319.67	-1	-9.99	-0.99
1964	10	1964.7896	316.87	319.93	-1	-9.99	-0.99
1964	11	1964.8743	317.68	319.59	-1	-9.99	-0.99
1964	12	1964.9563	318.71	319.49	-1	-9.99	-0.99
1965	1	1965.0411	319.44	319.38	-1	-9.99	-0.99
1965	2	1965.1260	320.44	319.79	-1	-9.99	-0.99
1965	3	1965.2027	320.89	319.59	-1	-9.99	-0.99
1965	4	1965.2877	322.14	319.79	-1	-9.99	-0.99
1965	5	1965.3699	322.17	319.28	-1	-9.99	-0.99
1965	6	1965.4548	321.87	319.68	-1	-9.99	-0.99
1965	7	1965.5370	321.21	320.53	-1	-9.99	-0.99
1965	8	1965.6219	318.87	320.18	-1	-9.99	-0.99
1965	9	1965.7068	317.82	320.78	-1	-9.99	-0.99
1965	10	1965.7890	317.30	320.37	-1	-9.99	-0.99
1965	11	1965.8740	318.87	320.79	-1	-9.99	-0.99
1965	12	1965.9562	319.42	320.20	-1	-9.99	-0.99
1966	1	1966.0411	320.62	320.57	-1	-9.99	-0.99
1966	2	1966.1260	321.60	320.94	-1	-9.99	-0.99
1966	3	1966.2027	322.39	321.08	-1	-9.99	-0.99
1966	4	1966.2877	323.70	321.34	-1	-9.99	-0.99

1966	5	1966.3699	324.08	321.18	-1	-9.99	-0.99
1966	6	1966.4548	323.75	321.55	-1	-9.99	-0.99
1966	7	1966.5370	322.37	321.69	-1	-9.99	-0.99
1966	8	1966.6219	320.36	321.68	-1	-9.99	-0.99
1966	9	1966.7068	318.64	321.61	-1	-9.99	-0.99
1966	10	1966.7890	318.10	321.18	-1	-9.99	-0.99
1966	11	1966.8740	319.78	321.71	-1	-9.99	-0.99
1966	12	1966.9562	321.02	321.81	-1	-9.99	-0.99
1967	1	1967.0411	322.33	322.28	-1	-9.99	-0.99
1967	2	1967.1260	322.50	321.83	-1	-9.99	-0.99
1967	3	1967.2027	323.03	321.72	-1	-9.99	-0.99
1967	4	1967.2877	324.41	322.05	-1	-9.99	-0.99
1967	5	1967.3699	325.00	322.09	-1	-9.99	-0.99
1967	6	1967.4548	324.09	321.89	-1	-9.99	-0.99
1967	7	1967.5370	322.54	321.86	-1	-9.99	-0.99
1967	8	1967.6219	320.92	322.24	-1	-9.99	-0.99
1967	9	1967.7068	319.25	322.24	-1	-9.99	-0.99
1967	10	1967.7890	319.39	322.48	-1	-9.99	-0.99
1967	11	1967.8740	320.73	322.66	-1	-9.99	-0.99
1967	12	1967.9562	321.96	322.74	-1	-9.99	-0.99
1968	1	1968.0410	322.57	322.51	-1	-9.99	-0.99
1968	2	1968.1257	323.15	322.48	-1	-9.99	-0.99
1968	3	1968.2049	323.89	322.55	-1	-9.99	-0.99
1968	4	1968.2896	325.02	322.63	-1	-9.99	-0.99
1968	5	1968.3716	325.57	322.66	-1	-9.99	-0.99
1968	6	1968.4563	325.36	323.17	-1	-9.99	-0.99
1968	7	1968.5383	324.14	323.48	-1	-9.99	-0.99
1968	8	1968.6230	322.11	323.46	-1	-9.99	-0.99
1968	9	1968.7077	320.33	323.33	-1	-9.99	-0.99
1968	10	1968.7896	320.25	323.34	-1	-9.99	-0.99
1968	11	1968.8743	321.32	323.26	-1	-9.99	-0.99
1968	12	1968.9563	322.89	323.68	-1	-9.99	-0.99
1969	1	1969.0411	324.00	323.95	-1	-9.99	-0.99
1969	2	1969.1260	324.41	323.75	-1	-9.99	-0.99
1969	3	1969.2027	325.63	324.31	-1	-9.99	-0.99
1969	4	1969.2877	326.66	324.28	-1	-9.99	-0.99
1969	5	1969.3699	327.38	324.46	-1	-9.99	-0.99
1969	6	1969.4548	326.71	324.49	-1	-9.99	-0.99
1969	7	1969.5370	325.88	325.19	-1	-9.99	-0.99
1969	8	1969.6219	323.66	324.99	-1	-9.99	-0.99
1969	9	1969.7068	322.38	325.38	-1	-9.99	-0.99
1969	10	1969.7890	321.78	324.89	-1	-9.99	-0.99
1969	11	1969.8740	322.85	324.80	-1	-9.99	-0.99
1969	12	1969.9562	324.11	324.91	-1	-9.99	-0.99
1970	1	1970.0411	325.06	325.01	-1	-9.99	-0.99
1970	2	1970.1260	325.99	325.31	-1	-9.99	-0.99
1970	3	1970.2027	326.93	325.61	-1	-9.99	-0.99
1970	4	1970.2877	328.13	325.75	-1	-9.99	-0.99
1970	5	1970.3699	328.08	325.15	-1	-9.99	-0.99

1970	6	1970.4548	327.67	325.44	-1	-9.99	-0.99
1970	7	1970.5370	326.34	325.65	-1	-9.99	-0.99
1970	8	1970.6219	324.68	326.02	-1	-9.99	-0.99
1970	9	1970.7068	323.10	326.11	-1	-9.99	-0.99
1970	10	1970.7890	323.06	326.18	-1	-9.99	-0.99
1970	11	1970.8740	324.01	325.96	-1	-9.99	-0.99
1970	12	1970.9562	325.13	325.93	-1	-9.99	-0.99
1971	1	1971.0411	326.17	326.12	-1	-9.99	-0.99
1971	2	1971.1260	326.69	326.01	-1	-9.99	-0.99
1971	3	1971.2027	327.18	325.85	-1	-9.99	-0.99
1971	4	1971.2877	327.78	325.39	-1	-9.99	-0.99
1971	5	1971.3699	328.93	325.99	-1	-9.99	-0.99
1971	6	1971.4548	328.57	326.34	-1	-9.99	-0.99
1971	7	1971.5370	327.36	326.67	-1	-9.99	-0.99
1971	8	1971.6219	325.43	326.77	-1	-9.99	-0.99
1971	9	1971.7068	323.36	326.38	-1	-9.99	-0.99
1971	10	1971.7890	323.56	326.69	-1	-9.99	-0.99
1971	11	1971.8740	324.80	326.75	-1	-9.99	-0.99
1971	12	1971.9562	326.01	326.81	-1	-9.99	-0.99
1972	1	1972.0410	326.77	326.71	-1	-9.99	-0.99
1972	2	1972.1257	327.63	326.96	-1	-9.99	-0.99
1972	3	1972.2049	327.75	326.39	-1	-9.99	-0.99
1972	4	1972.2896	329.72	327.30	-1	-9.99	-0.99
1972	5	1972.3716	330.07	327.12	-1	-9.99	-0.99
1972	6	1972.4563	329.09	326.87	-1	-9.99	-0.99
1972	7	1972.5383	328.04	327.38	-1	-9.99	-0.99
1972	8	1972.6230	326.32	327.69	-1	-9.99	-0.99
1972	9	1972.7077	324.84	327.88	-1	-9.99	-0.99
1972	10	1972.7896	325.20	328.33	-1	-9.99	-0.99
1972	11	1972.8743	326.50	328.46	-1	-9.99	-0.99
1972	12	1972.9563	327.55	328.35	-1	-9.99	-0.99
1973	1	1973.0411	328.55	328.49	-1	-9.99	-0.99
1973	2	1973.1260	329.57	328.89	-1	-9.99	-0.99
1973	3	1973.2027	330.30	328.97	-1	-9.99	-0.99
1973	4	1973.2877	331.50	329.10	-1	-9.99	-0.99
1973	5	1973.3699	332.48	329.52	-1	-9.99	-0.99
1973	6	1973.4548	332.07	329.83	-1	-9.99	-0.99
1973	7	1973.5370	330.87	330.18	-1	-9.99	-0.99
1973	8	1973.6219	329.31	330.66	-1	-9.99	-0.99
1973	9	1973.7068	327.52	330.56	-1	-9.99	-0.99
1973	10	1973.7890	327.19	330.33	-1	-9.99	-0.99
1973	11	1973.8740	328.17	330.13	-1	-9.99	-0.99
1973	12	1973.9562	328.65	329.45	-1	-9.99	-0.99
1974	1	1974.0411	329.36	329.30	-1	-9.99	-0.99
1974	2	1974.1260	330.71	330.03	-1	-9.99	-0.99
1974	3	1974.2027	331.49	330.15	-1	-9.99	-0.99
1974	4	1974.2877	332.65	330.24	-1	-9.99	-0.99
1974	5	1974.3750	333.19	330.22	13	0.31	0.16
1974	6	1974.4583	332.20	329.79	25	0.37	0.14

1974	7	1974.5417	331.07	330.21	24	0.24	0.09
1974	8	1974.6250	329.15	330.54	26	0.31	0.12
1974	9	1974.7083	327.33	330.44	22	0.47	0.19
1974	10	1974.7917	327.28	330.53	24	0.22	0.09
1974	11	1974.8750	328.31	330.50	26	0.43	0.16
1974	12	1974.9583	329.58	330.54	29	0.29	0.10
1975	1	1975.0417	330.73	330.84	29	0.43	0.15
1975	2	1975.1250	331.46	330.85	26	0.46	0.17
1975	3	1975.2083	331.94	330.37	17	0.33	0.15
1975	4	1975.2917	333.11	330.53	23	0.59	0.24
1975	5	1975.3750	333.95	330.98	28	0.35	0.13
1975	6	1975.4583	333.42	331.01	27	0.48	0.18
1975	7	1975.5417	331.97	331.12	24	0.45	0.18
1975	8	1975.6250	329.95	331.33	24	0.47	0.18
1975	9	1975.7083	328.49	331.60	22	0.53	0.22
1975	10	1975.7917	328.36	331.61	11	0.21	0.12
1975	11	1975.8750	329.38	331.57	18	0.31	0.14
1975	12	1975.9583	330.78	331.74	-1	-9.99	0.00
1976	1	1976.0417	331.56	331.67	19	0.23	0.10
1976	2	1976.1250	332.74	332.14	22	0.49	0.20
1976	3	1976.2083	333.36	331.79	18	0.52	0.23
1976	4	1976.2917	334.74	332.16	18	0.77	0.35
1976	5	1976.3750	334.72	331.75	21	0.56	0.23
1976	6	1976.4583	333.97	331.56	15	0.21	0.10
1976	7	1976.5417	333.08	332.23	15	0.24	0.12
1976	8	1976.6250	330.68	332.07	23	0.51	0.20
1976	9	1976.7083	328.96	332.07	13	0.69	0.37
1976	10	1976.7917	328.72	331.98	19	0.57	0.25
1976	11	1976.8750	330.16	332.35	25	0.36	0.14
1976	12	1976.9583	331.62	332.59	20	0.38	0.16
1977	1	1977.0417	332.68	332.77	23	0.40	0.16
1977	2	1977.1250	333.17	332.58	20	0.34	0.15
1977	3	1977.2083	334.96	333.40	23	0.51	0.21
1977	4	1977.2917	336.14	333.54	20	0.50	0.21
1977	5	1977.3750	336.93	334.00	20	0.31	0.13
1977	6	1977.4583	336.17	333.79	22	0.40	0.16
1977	7	1977.5417	334.89	334.01	20	0.23	0.10
1977	8	1977.6250	332.56	333.91	18	0.46	0.21
1977	9	1977.7083	331.29	334.36	19	0.46	0.20
1977	10	1977.7917	331.28	334.51	23	0.29	0.12
1977	11	1977.8750	332.46	334.68	21	0.43	0.18
1977	12	1977.9583	333.60	334.58	25	0.36	0.14
1978	1	1978.0417	334.94	335.01	22	0.52	0.21
1978	2	1978.1250	335.26	334.60	25	0.50	0.19
1978	3	1978.2083	336.66	335.00	28	0.59	0.21
1978	4	1978.2917	337.69	335.07	18	0.44	0.20
1978	5	1978.3750	338.02	335.08	26	0.46	0.17
1978	6	1978.4583	338.01	335.60	17	0.31	0.15
1978	7	1978.5417	336.50	335.65	20	0.32	0.14

1978	8	1978.6250	334.42	335.87	19	0.32	0.14
1978	9	1978.7083	332.36	335.51	17	0.75	0.35
1978	10	1978.7917	332.45	335.72	21	0.34	0.14
1978	11	1978.8750	333.76	335.99	24	0.25	0.10
1978	12	1978.9583	334.91	335.87	26	0.33	0.12
1979	1	1979.0417	336.14	336.22	27	0.55	0.20
1979	2	1979.1250	336.69	336.00	25	0.30	0.11
1979	3	1979.2083	338.27	336.56	21	0.63	0.26
1979	4	1979.2917	338.82	336.11	24	0.67	0.26
1979	5	1979.3750	339.24	336.24	20	0.50	0.22
1979	6	1979.4583	339.26	336.83	19	0.35	0.15
1979	7	1979.5417	337.54	336.69	26	0.59	0.22
1979	8	1979.6250	335.72	337.20	24	0.60	0.23
1979	9	1979.7083	333.97	337.19	19	0.65	0.29
1979	10	1979.7917	334.24	337.57	25	0.42	0.16
1979	11	1979.8750	335.32	337.59	27	0.30	0.11
1979	12	1979.9583	336.81	337.83	22	0.23	0.09
1980	1	1980.0417	337.90	338.13	29	0.57	0.20
1980	2	1980.1250	338.34	337.85	26	0.49	0.18
1980	3	1980.2083	340.07	338.51	23	0.54	0.22
1980	4	1980.2917	340.93	338.31	24	0.29	0.11
1980	5	1980.3750	341.45	338.40	24	0.54	0.21
1980	6	1980.4583	341.36	338.85	20	0.39	0.17
1980	7	1980.5417	339.45	338.56	26	0.60	0.22
1980	8	1980.6250	337.67	339.07	16	1.05	0.50
1980	9	1980.7083	336.25	339.38	15	0.69	0.34
1980	10	1980.7917	336.14	339.40	26	0.26	0.10
1980	11	1980.8750	337.30	339.46	27	0.26	0.10
1980	12	1980.9583	338.29	339.26	24	0.25	0.10
1981	1	1981.0417	339.29	339.42	28	0.39	0.14
1981	2	1981.1250	340.55	339.98	25	0.65	0.25
1981	3	1981.2083	341.63	340.08	25	0.48	0.19
1981	4	1981.2917	342.60	339.98	26	0.46	0.17
1981	5	1981.3750	343.04	339.97	30	0.19	0.07
1981	6	1981.4583	342.54	340.06	25	0.29	0.11
1981	7	1981.5417	340.82	339.92	24	0.46	0.18
1981	8	1981.6250	338.48	339.87	25	0.48	0.18
1981	9	1981.7083	336.95	340.17	27	0.55	0.20
1981	10	1981.7917	337.05	340.39	25	0.39	0.15
1981	11	1981.8750	338.58	340.75	26	0.31	0.12
1981	12	1981.9583	339.91	340.85	20	0.28	0.12
1982	1	1982.0417	340.93	341.09	28	0.30	0.11
1982	2	1982.1250	341.76	341.16	24	0.49	0.19
1982	3	1982.2083	342.78	341.18	17	0.41	0.19
1982	4	1982.2917	343.96	341.32	7	0.42	0.31
1982	5	1982.3750	344.77	341.67	27	0.37	0.14
1982	6	1982.4583	343.88	341.43	27	0.37	0.14
1982	7	1982.5417	342.42	341.61	28	0.35	0.13
1982	8	1982.6250	340.24	341.64	25	0.61	0.23

1982	9	1982.7083	338.37	341.56	21	0.59	0.25
1982	10	1982.7917	338.41	341.77	26	0.50	0.19
1982	11	1982.8750	339.44	341.59	24	0.39	0.15
1982	12	1982.9583	340.78	341.71	26	0.30	0.11
1983	1	1983.0417	341.57	341.75	28	0.47	0.17
1983	2	1983.1250	342.79	342.25	24	0.37	0.15
1983	3	1983.2083	343.37	341.85	27	0.88	0.32
1983	4	1983.2917	345.40	342.76	23	0.29	0.12
1983	5	1983.3750	346.14	342.97	28	0.51	0.19
1983	6	1983.4583	345.76	343.30	20	0.30	0.13
1983	7	1983.5417	344.32	343.56	22	0.57	0.23
1983	8	1983.6250	342.51	343.89	16	0.73	0.35
1983	9	1983.7083	340.46	343.59	15	0.50	0.25
1983	10	1983.7917	340.53	343.86	20	0.31	0.13
1983	11	1983.8750	341.79	343.92	27	0.33	0.12
1983	12	1983.9583	343.20	344.12	21	0.25	0.10
1984	1	1984.0417	344.21	344.32	23	0.40	0.16
1984	2	1984.1250	344.92	344.39	23	0.32	0.13
1984	3	1984.2083	345.68	344.26	19	0.30	0.13
1984	4	1984.2917	347.38	344.75	2	-9.99	0.00
1984	5	1984.3750	347.77	344.59	20	0.42	0.18
1984	6	1984.4583	347.16	344.73	20	0.31	0.13
1984	7	1984.5417	345.79	345.02	18	0.33	0.15
1984	8	1984.6250	343.74	345.12	12	0.45	0.25
1984	9	1984.7083	341.59	344.76	14	0.72	0.37
1984	10	1984.7917	341.86	345.19	12	0.36	0.20
1984	11	1984.8750	343.31	345.41	18	0.41	0.19
1984	12	1984.9583	345.00	345.88	14	0.53	0.27
1985	1	1985.0417	345.48	345.59	25	0.38	0.14
1985	2	1985.1250	346.41	345.92	15	0.37	0.18
1985	3	1985.2083	347.91	346.56	17	0.34	0.16
1985	4	1985.2917	348.66	346.08	21	0.61	0.25
1985	5	1985.3750	349.28	346.12	20	0.51	0.22
1985	6	1985.4583	348.65	346.23	21	0.34	0.14
1985	7	1985.5417	346.90	346.08	17	0.36	0.17
1985	8	1985.6250	345.26	346.57	16	0.57	0.27
1985	9	1985.7083	343.47	346.59	24	0.57	0.22
1985	10	1985.7917	343.35	346.60	20	0.29	0.13
1985	11	1985.8750	344.73	346.82	21	0.40	0.17
1985	12	1985.9583	346.12	347.04	26	0.62	0.23
1986	1	1986.0417	346.78	346.82	25	0.31	0.12
1986	2	1986.1250	347.48	346.98	25	0.45	0.17
1986	3	1986.2083	348.25	346.93	16	0.70	0.34
1986	4	1986.2917	349.86	347.29	19	0.38	0.17
1986	5	1986.3750	350.52	347.42	18	0.31	0.14
1986	6	1986.4583	349.98	347.61	17	0.25	0.11
1986	7	1986.5417	348.25	347.43	20	0.47	0.20
1986	8	1986.6250	346.17	347.51	18	0.48	0.21
1986	9	1986.7083	345.48	348.61	17	0.63	0.29

1986	10	1986.7917	344.82	348.04	25	0.32	0.12
1986	11	1986.8750	346.22	348.28	21	0.30	0.13
1986	12	1986.9583	347.48	348.36	24	0.35	0.14
1987	1	1987.0417	348.73	348.66	25	0.46	0.17
1987	2	1987.1250	348.92	348.24	25	0.58	0.22
1987	3	1987.2083	349.81	348.39	21	0.35	0.15
1987	4	1987.2917	351.40	348.84	26	0.68	0.25
1987	5	1987.3750	352.15	349.09	28	0.37	0.13
1987	6	1987.4583	351.58	349.29	22	0.21	0.09
1987	7	1987.5417	350.21	349.51	17	0.73	0.34
1987	8	1987.6250	348.20	349.65	15	0.85	0.42
1987	9	1987.7083	346.66	349.85	23	0.61	0.24
1987	10	1987.7917	346.72	349.96	22	0.41	0.17
1987	11	1987.8750	348.08	350.15	23	0.33	0.13
1987	12	1987.9583	349.28	350.14	27	0.20	0.08
1988	1	1988.0417	350.51	350.49	24	0.21	0.08
1988	2	1988.1250	351.70	350.99	23	0.57	0.23
1988	3	1988.2083	352.50	350.99	25	0.78	0.30
1988	4	1988.2917	353.67	351.03	27	0.48	0.18
1988	5	1988.3750	354.35	351.22	28	0.37	0.13
1988	6	1988.4583	353.88	351.55	26	0.30	0.11
1988	7	1988.5417	352.80	352.16	27	0.49	0.18
1988	8	1988.6250	350.49	352.01	26	0.62	0.23
1988	9	1988.7083	348.97	352.18	26	0.47	0.18
1988	10	1988.7917	349.37	352.62	26	0.31	0.12
1988	11	1988.8750	350.42	352.53	25	0.20	0.08
1988	12	1988.9583	351.62	352.52	28	0.36	0.13
1989	1	1989.0417	353.07	352.99	28	0.45	0.16
1989	2	1989.1250	353.43	352.69	25	0.38	0.15
1989	3	1989.2083	354.08	352.60	29	0.53	0.19
1989	4	1989.2917	355.72	353.07	28	0.47	0.17
1989	5	1989.3750	355.95	352.78	27	0.49	0.18
1989	6	1989.4583	355.44	353.06	26	0.42	0.16
1989	7	1989.5417	354.05	353.38	26	0.41	0.15
1989	8	1989.6250	351.84	353.43	25	0.48	0.18
1989	9	1989.7083	350.09	353.37	24	0.69	0.27
1989	10	1989.7917	350.33	353.57	25	0.34	0.13
1989	11	1989.8750	351.55	353.68	27	0.36	0.13
1989	12	1989.9583	352.91	353.84	27	0.48	0.18
1990	1	1990.0417	353.86	353.78	25	0.34	0.13
1990	2	1990.1250	355.10	354.37	28	0.66	0.24
1990	3	1990.2083	355.75	354.26	27	0.57	0.21
1990	4	1990.2917	356.38	353.76	28	0.55	0.20
1990	5	1990.3750	357.38	354.23	28	0.30	0.11
1990	6	1990.4583	356.39	354.02	29	0.40	0.14
1990	7	1990.5417	354.89	354.24	30	0.89	0.31
1990	8	1990.6250	353.06	354.68	22	0.62	0.25
1990	9	1990.7083	351.38	354.69	27	0.72	0.26
1990	10	1990.7917	351.69	354.94	28	0.30	0.11

1990	11	1990.8750	353.14	355.18	24	0.20	0.08
1990	12	1990.9583	354.41	355.26	28	0.51	0.19
1991	1	1991.0417	354.93	354.91	28	0.51	0.18
1991	2	1991.1250	355.82	355.11	26	0.54	0.20
1991	3	1991.2083	357.33	355.79	30	0.73	0.25
1991	4	1991.2917	358.77	356.13	30	0.66	0.23
1991	5	1991.3750	359.23	356.10	29	0.52	0.19
1991	6	1991.4583	358.23	355.88	29	0.30	0.11
1991	7	1991.5417	356.30	355.69	24	0.46	0.18
1991	8	1991.6250	353.97	355.59	23	0.39	0.15
1991	9	1991.7083	352.34	355.66	27	0.37	0.14
1991	10	1991.7917	352.43	355.69	27	0.25	0.09
1991	11	1991.8750	353.89	355.87	28	0.25	0.09
1991	12	1991.9583	355.21	356.02	30	0.34	0.12
1992	1	1992.0417	356.34	356.29	31	0.60	0.21
1992	2	1992.1250	357.21	356.47	27	0.56	0.21
1992	3	1992.2083	357.97	356.38	24	0.72	0.28
1992	4	1992.2917	359.22	356.51	27	0.53	0.20
1992	5	1992.3750	359.71	356.52	26	0.74	0.28
1992	6	1992.4583	359.44	357.07	30	0.49	0.17
1992	7	1992.5417	357.15	356.58	25	0.63	0.24
1992	8	1992.6250	354.99	356.67	24	0.62	0.24
1992	9	1992.7083	353.01	356.36	25	0.98	0.38
1992	10	1992.7917	353.41	356.72	29	0.56	0.20
1992	11	1992.8750	354.42	356.48	29	0.34	0.12
1992	12	1992.9583	355.68	356.50	31	0.32	0.11
1993	1	1993.0417	357.10	357.06	28	0.58	0.21
1993	2	1993.1250	357.42	356.54	28	0.49	0.18
1993	3	1993.2083	358.59	356.88	30	0.72	0.25
1993	4	1993.2917	359.39	356.71	25	0.53	0.20
1993	5	1993.3750	360.30	357.14	30	0.45	0.16
1993	6	1993.4583	359.64	357.24	28	0.35	0.13
1993	7	1993.5417	357.45	356.87	25	0.78	0.30
1993	8	1993.6250	355.76	357.44	27	0.62	0.23
1993	9	1993.7083	354.14	357.51	23	0.73	0.29
1993	10	1993.7917	354.23	357.61	28	0.29	0.11
1993	11	1993.8750	355.53	357.65	29	0.26	0.09
1993	12	1993.9583	357.03	357.92	29	0.28	0.10
1994	1	1994.0417	358.36	358.25	27	0.33	0.12
1994	2	1994.1250	359.04	358.21	25	0.50	0.19
1994	3	1994.2083	360.11	358.41	29	0.82	0.29
1994	4	1994.2917	361.36	358.59	28	0.50	0.18
1994	5	1994.3750	361.78	358.59	30	0.45	0.16
1994	6	1994.4583	360.94	358.57	27	0.30	0.11
1994	7	1994.5417	359.51	358.91	31	0.41	0.14
1994	8	1994.6250	357.59	359.29	24	0.43	0.17
1994	9	1994.7083	355.86	359.31	24	0.58	0.23
1994	10	1994.7917	356.21	359.63	28	0.28	0.10
1994	11	1994.8750	357.65	359.80	28	0.51	0.18

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1995	2	1995.1250	361.00	360.18	28	0.52	0.19
1995	3	1995.2083	361.98	360.37	29	0.78	0.28
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1996	3	1996.2083	364.28	362.64	28	0.67	0.24
1996	4	1996.2917	364.69	361.99	29	0.59	0.21
1996	5	1996.3750	365.25	362.23	30	0.57	0.20
1996	6	1996.4583	365.06	362.82	30	0.38	0.13
1996	7	1996.5417	363.69	362.98	31	0.32	0.11
1996	8	1996.6250	361.55	363.13	27	0.49	0.18
1996	9	1996.7083	359.69	363.14	25	0.75	0.29
1996	10	1996.7917	359.72	363.12	29	0.32	0.11
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1996	12	1996.9583	362.39	363.23	29	0.36	0.13
1997	1	1997.0417	363.24	363.03	31	0.40	0.14
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2005	11	2005.8750	378.54	380.69	23	0.45	0.18
2005	12	2005.9583	380.31	381.09	26	0.39	0.15
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2006	9	2006.7083	379.04	382.35	25	0.42	0.16
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2007	11	2007.8750	382.70	384.90	30	0.31	0.11
2007	12	2007.9583	384.19	385.07	22	0.34	0.14
2008	1	2008.0417	385.78	385.54	31	0.56	0.19
2008	2	2008.1250	386.06	385.20	26	0.58	0.22
2008	3	2008.2083	386.28	384.72	30	0.60	0.21
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2009	8	2009.6250	386.29	387.99	28	0.62	0.22
2009	9	2009.7083	384.95	388.22	28	0.56	0.20
2009	10	2009.7917	384.64	387.88	30	0.31	0.11
2009	11	2009.8750	386.23	388.36	30	0.29	0.10
2009	12	2009.9583	387.63	388.43	20	0.47	0.20
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2010	2	2010.1250	390.41	389.47	20	1.31	0.56
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2010	4	2010.2917	392.67	390.12	26	0.65	0.24
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2010	6	2010.4583	392.38	390.10	28	0.42	0.15
2010	7	2010.5417	390.41	389.93	29	0.47	0.17
2010	8	2010.6250	388.54	390.21	26	0.41	0.16
2010	9	2010.7083	387.03	390.32	29	0.55	0.19
2010	10	2010.7917	387.43	390.72	31	0.27	0.09
2010	11	2010.8750	388.87	390.99	29	0.42	0.15
2010	12	2010.9583	389.99	390.80	29	0.47	0.17
2011	1	2011.0417	391.50	391.19	29	0.88	0.31
2011	2	2011.1250	392.05	391.12	28	0.47	0.17
2011	3	2011.2083	392.80	391.27	29	0.97	0.35

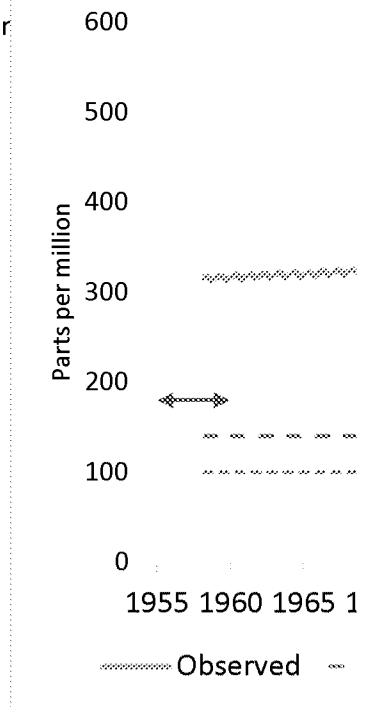
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2011	8	2011.6250	390.33	392.04	27	0.42	0.15
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2011	12	2011.9583	392.06	392.86	26	0.37	0.14
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2012	9	2012.7083	391.32	394.75	26	0.42	0.16
2012	10	2012.7917	391.27	394.64	28	0.23	0.08
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2013	5	2013.3750	400.02	396.64	28	0.37	0.13
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2013	8	2013.6250	395.39	397.27	27	0.45	0.16
2013	9	2013.7083	393.72	397.24	26	0.35	0.13
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2014	9	2014.7083	395.54	399.11	21	0.54	0.23
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2015	12	2015.9583	402.06	402.72	30	0.67	0.23
2016	1	2016.0417	402.73	402.45	27	0.56	0.21
2016	2	2016.1250	404.25	403.40	25	1.11	0.43
2016	3	2016.2083	405.06	403.54	28	0.81	0.29
2016	4	2016.2917	407.60	404.77	23	1.04	0.41
2016	5	2016.3750	407.90	404.41	29	0.50	0.18
2016	6	2016.4583	406.99	404.59	26	0.60	0.23
2016	7	2016.5417	404.59	404.24	28	0.88	0.32
2016	8	2016.6250	402.45	404.41	24	0.60	0.23
2016	9	2016.7083	401.23	404.85	25	0.44	0.17
2016	10	2016.7917	401.79	405.23	29	0.30	0.11
2016	11	2016.8750	403.72	405.74	27	0.72	0.26
2016	12	2016.9583	404.64	405.33	29	0.44	0.16
2017	1	2017.0417	406.36	406.04	27	0.68	0.25
2017	2	2017.1250	406.65	405.80	26	0.71	0.27
2017	3	2017.2083	407.53	406.05	24	1.03	0.40
2017	4	2017.2917	409.22	406.37	26	0.86	0.32
2017	5	2017.3750	409.89	406.37	27	0.57	0.21
2017	6	2017.4583	409.08	406.68	26	0.54	0.20
2017	7	2017.5417	407.33	407.01	28	0.61	0.22
2017	8	2017.6250	405.32	407.31	29	0.32	0.12
2017	9	2017.7083	403.57	407.17	26	0.37	0.14
2017	10	2017.7917	403.82	407.23	27	0.30	0.11
2017	11	2017.8750	405.31	407.36	26	0.41	0.15
2017	12	2017.9583	407.00	407.71	31	0.57	0.20
2018	1	2018.0417	408.15	407.83	29	0.55	0.19
2018	2	2018.1250	408.52	407.61	28	0.52	0.19
2018	3	2018.2083	409.59	408.06	29	0.65	0.23
2018	4	2018.2917	410.45	407.65	21	0.90	0.38
2018	5	2018.3750	411.44	407.98	24	0.86	0.33
2018	6	2018.4583	410.99	408.60	29	0.61	0.22
2018	7	2018.5417	408.90	408.60	27	0.46	0.17
2018	8	2018.6250	407.16	409.17	31	0.28	0.10
2018	9	2018.7083	405.71	409.30	29	0.45	0.16
2018	10	2018.7917	406.19	409.56	30	0.32	0.11
2018	11	2018.8750	408.21	410.24	24	0.56	0.22
2018	12	2018.9583	409.27	409.99	30	0.50	0.17
2019	1	2019.0417	411.03	410.69	26	1.26	0.47
2019	2	2019.1250	411.96	410.97	27	1.14	0.42
2019	3	2019.2083	412.18	410.71	28	1.12	0.40
2019	4	2019.2917	413.54	410.92	27	0.60	0.22
2019	5	2019.3750	414.86	411.47	28	0.50	0.18

2019	6	2019.4583	414.15	411.74	27	0.36	0.13
2019	7	2019.5417	411.96	411.64	25	0.81	0.31
2019	8	2019.6250	410.17	412.10	29	0.32	0.11
2019	9	2019.7083	408.76	412.26	29	0.35	0.13
2019	10	2019.7917	408.74	412.09	29	0.31	0.11
2019	11	2019.8750	410.47	412.50	26	0.40	0.15
2019	12	2019.9583	411.97	412.71	31	0.40	0.14
2020	1	2020.0417	413.59	413.22	29	0.73	0.26
2020	2	2020.1250	414.32	413.40	28	0.69	0.25
2020	3	2020.2083	414.72	413.35	26	0.32	0.12
2020	4	2020.2917	416.42	413.92	28	0.65	0.24
2020	5	2020.3750	417.28	413.98	27	0.61	0.23
2020	6	2020.4583	416.58	414.15	27	0.44	0.16
2020	7	2020.5417	414.58	414.19	30	0.57	0.20
2020	8	2020.6250	412.75	414.60	25	0.25	0.10
2020	9	2020.7083	411.50	414.90	29	0.31	0.11
2020	10	2020.7917	411.49	414.79	30	0.22	0.08
2020	11	2020.8750	413.10	415.11	27	0.81	0.30
2020	12	2020.9583	414.23	414.91	30	0.48	0.17
2021	1	2021.0417	415.49	415.23	29	0.44	0.16
2021	2	2021.1250	416.72	415.80	28	1.02	0.37
2021	3	2021.2083	417.61	416.17	28	0.86	0.31
2021	4	2021.2917	419.01	416.59	24	1.12	0.44
2021	5	2021.3750	419.09	415.88	28	0.90	0.32
2021	6	2021.4583	418.93	416.48	29	0.65	0.23
2021	7	2021.5417	416.90	416.48	31	0.71	0.24
2021	8	2021.6250	414.42	416.27	25	0.74	0.28
2021	9	2021.7083	413.26	416.63	27	0.29	0.11
2021	10	2021.7917	413.90	417.14	29	0.35	0.12
2021	11	2021.8750	414.97	416.92	30	0.36	0.13
2021	12	2021.9583	416.67	417.37	28	0.48	0.17
2022	1	2022.0417	418.13	417.82	30	0.72	0.25
2022	2	2022.1250	419.24	418.31	27	0.92	0.34
2022	3	2022.2083	418.76	417.28	30	0.78	0.27
2022	4	2022.2917	420.19	417.66	28	0.86	0.31
2022	5	2022.3750	420.97	417.73	31	0.75	0.26
2022	6	2022.4583	420.94	418.53	28	0.30	0.11
2022	7	2022.5417	418.85	418.43	27	0.57	0.21
2022	8	2022.6250	417.15	419.01	27	0.37	0.13
2022	9	2022.7083	415.91	419.32	28	0.41	0.15
2022	10	2022.7917	415.74	419.03	30	0.27	0.10
2022	11	2022.8750	417.47	419.50	25	0.52	0.20
2022	12	2022.9583	418.99	419.71	24	0.57	0.22
2023	1	2023.0417	419.47	419.16	31	0.40	0.14
2023	2	2023.1250	420.31	419.38	23	0.70	0.28
2023	3	2023.2083	420.99	419.52	30	0.74	0.26
2023	4	2023.2917	423.31	420.78	27	0.56	0.21
2023	5	2023.3750	424.00	420.77	31	0.70	0.24
2023	6	2023.4583	423.68	421.26	29	0.57	0.20

2023	7	2023.5417	421.83	421.40	21	0.48	0.20
2023	8	2023.6250	419.68	421.55	21	0.45	0.19
2023	9	2023.7083	418.50	421.92	18	0.30	0.14
2023	10	2023.7917	418.82	422.12	27	0.47	0.17
2023	11	2023.8750	420.46	422.49	21	0.91	0.38
2023	12	2023.9583	421.86	422.57	20	0.69	0.29
2024	1	2024.0417	422.80	422.50	27	0.70	0.26
2024	2	2024.1250	424.55	423.63	22	1.24	0.51
2024	3	2024.2083	425.38	423.91	22	0.99	0.40
2024	4	2024.2917	426.51	423.98	22	0.99	0.40
2024	5	2024.3750	426.90	423.67	29	0.76	0.27
2024	6	2024.4583	426.91	424.50	20	0.65	0.28
2024	7	2024.5417	425.55	425.13	24	0.69	0.27
2024	8	2024.6250	422.99	424.85	22	1.08	0.44
2024	9	2024.7083	422.03	425.45	18	0.41	0.18
2024	10	2024.7917	422.38	425.68	22	0.35	0.14
2024	11	2024.8750	423.85	425.88	24	0.33	0.13
2024	12	2024.9583	425.40	426.12	28	0.70	0.25
2025	1	2025.0417	426.65	426.34	29	0.62	0.22
2025	2	2025.1250	427.09	426.16	24	0.64	0.25
2025	3	2025.2083	428.15	426.67	27	1.13	0.42
2025	4	2025.2917	429.64	427.11	23	0.73	0.29

Column2	Column3	Column5	Column7	Column8	Column9
Year	Month	Observed	C3 Threshc	C4 Threshc	Glacial minimur
1955	1				180
1955	2				180
1955	3				180
1955	4				180
1955	5				180
1955	6				180
1955	7				180
1955	8				180
1955	9				180
1955	10				180
1955	11				180
1955	12				180
1956	1				180
1956	2				180
1956	3				180
1956	4				180
1956	5				180
1956	6				180
1956	7				180
1956	8				180
1956	9				180
1956	10				180
1956	11				180
1956	12				180
1957	1				180
1957	2				180
1957	3				180
1957	4				180
1957	5				180
1957	6				180
1957	7				180
1957	8				180
1957	9				180
1957	10				180
1957	11				180
1957	12				180
1958	1				180
1958	2				180
1958	3	315.71	140	100	180
1958	4	317.45	140	100	180
1958	5	317.51	140	100	180
1958	6	317.27	140	100	180
1958	7	315.87	140	100	180
1958	8	314.93	140	100	180
1958	9	313.21	140	100	180



1958	10	312.42	140	100	180
1958	11	313.33	140	100	180
1958	12	314.67	140	100	180
1959	1	315.58	140	100	180
1959	2	316.49	140	100	180
1959	3	316.65	140	100	180
1959	4	317.72	140	100	180
1959	5	318.29	140	100	180
1959	6	318.15	140	100	180
1959	7	316.54	140	100	180
1959	8	314.8	140	100	180
1959	9	313.84	140	100	180
1959	10	313.33	140	100	180
1959	11	314.81	140	100	180
1959	12	315.58	140	100	180
1960	1	316.43	140	100	
1960	2	316.98	140	100	
1960	3	317.58	140	100	
1960	4	319.03	140	100	
1960	5	320.03	140	100	
1960	6	319.58	140	100	
1960	7	318.18	140	100	
1960	8	315.9	140	100	
1960	9	314.17	140	100	
1960	10	313.83	140	100	
1960	11	315	140	100	
1960	12	316.19	140	100	
1961	1	316.89	140	100	
1961	2	317.7	140	100	
1961	3	318.54	140	100	
1961	4	319.48	140	100	
1961	5	320.58	140	100	
1961	6	319.77	140	100	
1961	7	318.56	140	100	
1961	8	316.79	140	100	
1961	9	314.99	140	100	
1961	10	315.31	140	100	
1961	11	316.1	140	100	
1961	12	317.01	140	100	
1962	1	317.94	140	100	
1962	2	318.55	140	100	
1962	3	319.68	140	100	
1962	4	320.57	140	100	
1962	5	321.02	140	100	
1962	6	320.62	140	100	
1962	7	319.61	140	100	
1962	8	317.4	140	100	

Source: NASA gml.noaa.gov/ccgg,
<https://climate.nasa.gov/vital-sig>

1962	9	316.24	140	100
1962	10	315.42	140	100
1962	11	316.69	140	100
1962	12	317.7	140	100
1963	1	318.74	140	100
1963	2	319.07	140	100
1963	3	319.86	140	100
1963	4	321.38	140	100
1963	5	322.24	140	100
1963	6	321.49	140	100
1963	7	319.74	140	100
1963	8	317.77	140	100
1963	9	316.21	140	100
1963	10	315.99	140	100
1963	11	317.07	140	100
1963	12	318.35	140	100
1964	1	319.57	140	100
1964	2	320.04	140	100
1964	3	320.75	140	100
1964	4	321.84	140	100
1964	5	322.25	140	100
1964	6	321.89	140	100
1964	7	320.44	140	100
1964	8	318.69	140	100
1964	9	316.71	140	100
1964	10	316.87	140	100
1964	11	317.68	140	100
1964	12	318.71	140	100
1965	1	319.44	140	100
1965	2	320.44	140	100
1965	3	320.89	140	100
1965	4	322.14	140	100
1965	5	322.17	140	100
1965	6	321.87	140	100
1965	7	321.21	140	100
1965	8	318.87	140	100
1965	9	317.82	140	100
1965	10	317.3	140	100
1965	11	318.87	140	100
1965	12	319.42	140	100
1966	1	320.62	140	100
1966	2	321.6	140	100
1966	3	322.39	140	100
1966	4	323.7	140	100
1966	5	324.08	140	100
1966	6	323.75	140	100
1966	7	322.37	140	100

1966	8	320.36	140	100
1966	9	318.64	140	100
1966	10	318.1	140	100
1966	11	319.78	140	100
1966	12	321.02	140	100
1967	1	322.33	140	100
1967	2	322.5	140	100
1967	3	323.03	140	100
1967	4	324.41	140	100
1967	5	325	140	100
1967	6	324.09	140	100
1967	7	322.54	140	100
1967	8	320.92	140	100
1967	9	319.25	140	100
1967	10	319.39	140	100
1967	11	320.73	140	100
1967	12	321.96	140	100
1968	1	322.57	140	100
1968	2	323.15	140	100
1968	3	323.89	140	100
1968	4	325.02	140	100
1968	5	325.57	140	100
1968	6	325.36	140	100
1968	7	324.14	140	100
1968	8	322.11	140	100
1968	9	320.33	140	100
1968	10	320.25	140	100
1968	11	321.32	140	100
1968	12	322.89	140	100
1969	1	324	140	100
1969	2	324.41	140	100
1969	3	325.63	140	100
1969	4	326.66	140	100
1969	5	327.38	140	100
1969	6	326.71	140	100
1969	7	325.88	140	100
1969	8	323.66	140	100
1969	9	322.38	140	100
1969	10	321.78	140	100
1969	11	322.85	140	100
1969	12	324.11	140	100
1970	1	325.06	140	100
1970	2	325.99	140	100
1970	3	326.93	140	100
1970	4	328.13	140	100
1970	5	328.08	140	100
1970	6	327.67	140	100

1970	7	326.34	140	100
1970	8	324.68	140	100
1970	9	323.1	140	100
1970	10	323.06	140	100
1970	11	324.01	140	100
1970	12	325.13	140	100
1971	1	326.17	140	100
1971	2	326.69	140	100
1971	3	327.18	140	100
1971	4	327.78	140	100
1971	5	328.93	140	100
1971	6	328.57	140	100
1971	7	327.36	140	100
1971	8	325.43	140	100
1971	9	323.36	140	100
1971	10	323.56	140	100
1971	11	324.8	140	100
1971	12	326.01	140	100
1972	1	326.77	140	100
1972	2	327.63	140	100
1972	3	327.75	140	100
1972	4	329.72	140	100
1972	5	330.07	140	100
1972	6	329.09	140	100
1972	7	328.04	140	100
1972	8	326.32	140	100
1972	9	324.84	140	100
1972	10	325.2	140	100
1972	11	326.5	140	100
1972	12	327.55	140	100
1973	1	328.55	140	100
1973	2	329.57	140	100
1973	3	330.3	140	100
1973	4	331.5	140	100
1973	5	332.48	140	100
1973	6	332.07	140	100
1973	7	330.87	140	100
1973	8	329.31	140	100
1973	9	327.52	140	100
1973	10	327.19	140	100
1973	11	328.17	140	100
1973	12	328.65	140	100
1974	1	329.36	140	100
1974	2	330.71	140	100
1974	3	331.49	140	100
1974	4	332.65	140	100
1974	5	333.19	140	100

1974	6	332.2	140	100
1974	7	331.07	140	100
1974	8	329.15	140	100
1974	9	327.33	140	100
1974	10	327.28	140	100
1974	11	328.31	140	100
1974	12	329.58	140	100
1975	1	330.73	140	100
1975	2	331.46	140	100
1975	3	331.94	140	100
1975	4	333.11	140	100
1975	5	333.95	140	100
1975	6	333.42	140	100
1975	7	331.97	140	100
1975	8	329.95	140	100
1975	9	328.49	140	100
1975	10	328.36	140	100
1975	11	329.38	140	100
1975	12	330.78	140	100
1976	1	331.56	140	100
1976	2	332.74	140	100
1976	3	333.36	140	100
1976	4	334.74	140	100
1976	5	334.72	140	100
1976	6	333.97	140	100
1976	7	333.08	140	100
1976	8	330.68	140	100
1976	9	328.96	140	100
1976	10	328.72	140	100
1976	11	330.16	140	100
1976	12	331.62	140	100
1977	1	332.68	140	100
1977	2	333.17	140	100
1977	3	334.96	140	100
1977	4	336.14	140	100
1977	5	336.93	140	100
1977	6	336.17	140	100
1977	7	334.89	140	100
1977	8	332.56	140	100
1977	9	331.29	140	100
1977	10	331.28	140	100
1977	11	332.46	140	100
1977	12	333.6	140	100
1978	1	334.94	140	100
1978	2	335.26	140	100
1978	3	336.66	140	100
1978	4	337.69	140	100

1978	5	338.02	140	100
1978	6	338.01	140	100
1978	7	336.5	140	100
1978	8	334.42	140	100
1978	9	332.36	140	100
1978	10	332.45	140	100
1978	11	333.76	140	100
1978	12	334.91	140	100
1979	1	336.14	140	100
1979	2	336.69	140	100
1979	3	338.27	140	100
1979	4	338.82	140	100
1979	5	339.24	140	100
1979	6	339.26	140	100
1979	7	337.54	140	100
1979	8	335.72	140	100
1979	9	333.97	140	100
1979	10	334.24	140	100
1979	11	335.32	140	100
1979	12	336.81	140	100
1980	1	337.9	140	100
1980	2	338.34	140	100
1980	3	340.07	140	100
1980	4	340.93	140	100
1980	5	341.45	140	100
1980	6	341.36	140	100
1980	7	339.45	140	100
1980	8	337.67	140	100
1980	9	336.25	140	100
1980	10	336.14	140	100
1980	11	337.3	140	100
1980	12	338.29	140	100
1981	1	339.29	140	100
1981	2	340.55	140	100
1981	3	341.63	140	100
1981	4	342.6	140	100
1981	5	343.04	140	100
1981	6	342.54	140	100
1981	7	340.82	140	100
1981	8	338.48	140	100
1981	9	336.95	140	100
1981	10	337.05	140	100
1981	11	338.58	140	100
1981	12	339.91	140	100
1982	1	340.93	140	100
1982	2	341.76	140	100
1982	3	342.78	140	100

1982	4	343.96	140	100
1982	5	344.77	140	100
1982	6	343.88	140	100
1982	7	342.42	140	100
1982	8	340.24	140	100
1982	9	338.37	140	100
1982	10	338.41	140	100
1982	11	339.44	140	100
1982	12	340.78	140	100
1983	1	341.57	140	100
1983	2	342.79	140	100
1983	3	343.37	140	100
1983	4	345.4	140	100
1983	5	346.14	140	100
1983	6	345.76	140	100
1983	7	344.32	140	100
1983	8	342.51	140	100
1983	9	340.46	140	100
1983	10	340.53	140	100
1983	11	341.79	140	100
1983	12	343.2	140	100
1984	1	344.21	140	100
1984	2	344.92	140	100
1984	3	345.68	140	100
1984	4	347.38	140	100
1984	5	347.77	140	100
1984	6	347.16	140	100
1984	7	345.79	140	100
1984	8	343.74	140	100
1984	9	341.59	140	100
1984	10	341.86	140	100
1984	11	343.31	140	100
1984	12	345	140	100
1985	1	345.48	140	100
1985	2	346.41	140	100
1985	3	347.91	140	100
1985	4	348.66	140	100
1985	5	349.28	140	100
1985	6	348.65	140	100
1985	7	346.9	140	100
1985	8	345.26	140	100
1985	9	343.47	140	100
1985	10	343.35	140	100
1985	11	344.73	140	100
1985	12	346.12	140	100
1986	1	346.78	140	100
1986	2	347.48	140	100

1986	3	348.25	140	100
1986	4	349.86	140	100
1986	5	350.52	140	100
1986	6	349.98	140	100
1986	7	348.25	140	100
1986	8	346.17	140	100
1986	9	345.48	140	100
1986	10	344.82	140	100
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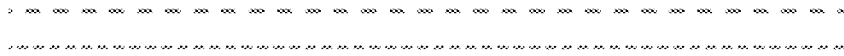
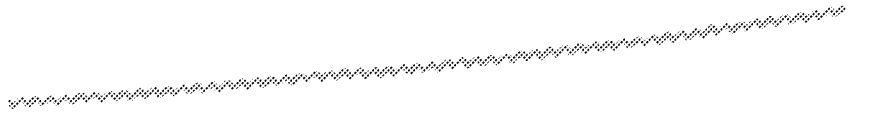
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1970 1975 1980 1985 1990 1995 2000 2005 2010 2015 2020 2025

--- C3 Threshold - - - - - C4 Threshold ◆◆◆◆◆ Glacial minimum

/trends/
ns/carbon-dioxide/?intent=121

17 April 2025

1.2 How Climate Conditions are Measured [JC]

The climate system consists of the global deep atmosphere, the full ocean and the upper layers of the land and ice surface - reservoirs of energy which are able to interact with each other on times scales up to centuries. Most climate concerns however are related to what happens at the surface where we live and grow our food. The directly-measured surface climate metrics that provide the longest record for analysis (generally since the late 19th century) are daily values of precipitation, i.e., rain and snow, and near-surface air temperature, i.e., the hottest and coldest values occurring in each 24-hour period (IPCC AR6 2.3.1.1.3 and 2.3.1.3.4). The amount of water vapor (humidity) in the atmosphere is also an important metric for determining heat content (IPCC AR6 2.3.1.3.2 and 2.3.1.3.3).

The number of weather patterns experienced by the natural climate system is essentially infinite so that a very long period of measurements is desirable to quantify natural variability with confidence [see 1.3]. However, with only 130+ years of quasi-large-scale surface observations we are presented with a fairly small time-sample of Earth's history from which to determine, for example, metrics such as extreme values or to assess whether changes may be related to increasing GHGs rather than natural variability. A critical question to address is whether the climate variations of the last 130 years (a very thin slice of climate history) represent a useful sample of all of the possible natural variations so that claims of significance (e.g., due to GHG forcing) may be made when a recent change is observed. Then, to this temporal impediment is the shortfall of spatial sampling with most of the global surface - even to this day - still unmonitored by *in situ* instrumentation which adds to the uncertainty of the values through time.

Surface temperature measurements are confounded by several heterogeneities in the record such as station relocations, instrument changes, instrument drifts/malfunctions, station closures, encroachment of temperature-altering infrastructure such as buildings, streets, deforestation, etc. All of these influences reduce confidence that the long-term, unadjusted values are stable enough for assessing small changes in the background climate. These non-climate temperature impacts, especially changes in the local environment, are significant and attempts to quantify their magnitudes are numerous (IPCC AR6 1.5.1, 2.3.1.1.3).

With the advent of vertical profiling techniques in the 20th century (balloons for the atmosphere, bathythermographs for the ocean, bore-holes for land and ice caps), a more comprehensive picture of the 3-dimensional climate system was made possible (IPCC AR6 2.3.1.2, 2.3.3.1., 2.3.1.1.2). These measurements are of critical importance because the fundamental metric for understanding changes caused by enhanced greenhouse gas (GHG) forcing is the number of heat units (joules) residing in the reservoirs of the climate system (atmosphere, ocean, near-surface land/ice) and how that number might be changing. The theory of GHG forcing indicates the number of joules should be increasing, primarily detected as rising temperatures in the full ocean and lower atmosphere (sfc to ~12km). From the 1970s

satellites have provided global coverage for the first-time of several climate metrics, including clouds, snow and ice cover, water vapor, aerosols, winds, incoming and outgoing energy, and the deep atmospheric temperature – the latter a key for detecting GHG influences as mentioned (IPCC AR6 2.3.1.2, 2.3.1.3.3).

US observations are also available of high-impact weather events which have been systematically recorded for such phenomena as hurricanes (since 1850 for Atlantic storms), strong tornadoes (since 1950s), floods, droughts, etc. (IPCC AR6 11.4-11.7). In addition to these relatively rapid events are changes that are slow such as sea level rise and ocean pH changes (IPCC AR6 9.6, 12.4.8, 3.6.2). Snow and sea ice extents have particular significance as indicators of climate change with measurements from satellites providing global coverage since 1978 to supplement surface and aircraft measurements beginning in earlier years (IPCC AR6 2.3.2). [Indirect or “proxy” measurements such as ice-cores and tree-rings, provide inferences of pre-instrumental weather but with considerable uncertainty, IPCC AR6 2.3.1.1.1].

Finally, climate conditions may be examined through global maps of climate metrics, called Reanalyses, that are produced by major weather services who utilize a modeling framework to synthesize observations (including all those mentioned above) into a depiction of the global weather, generally every 6 hours. The most confident depictions begin in late 1978 when satellites started providing significant global information, though there are still uncertainties as input data tends to change with time in quality and distribution (IPCC AR6 1.5.2). A summary of these observational systems that measure climate conditions is provided in IPCC AR6 T1.2.1, 1.5.1 and 1.5.2.

Chapter 8

~~Thoughts on Changes in short-term extreme temperature and precipitation events~~

Extremes in temperature and precipitation are generally events of short duration that often disrupt infrastructure and therefore human health and thriveability. Indeed, the ability of any surface-dwelling species to live productively is somewhat constrained by these near-surface air temperature or precipitation extremes which in essence create the bounding limits for survival. The issue here is whether these extremes, and their attendant potential danger, may be changing in response to increases in infrared-absorbing greenhouse gases (*GHGs*) (e.g., IPCC AR6 Seneviratne et al. 2021).

Unfortunately, the sample of time from which we are able to quantitatively analyze the variations of extreme events is quite brief, around 130 years. This period certainly does not begin to contain all of the extreme events that the climate system, ~~driven by the interaction of two turbulent and chaotic fluids (the atmosphere and ocean),~~ is able to generate. ~~One should appreciate that~~ Over geologic time the climate system has generated an (essentially) infinite variety of patterns and extremes which we humans have never observed, and thus which do not enter our databases from which extreme statistics are determined [see 6.4]. Thus, assuming that a new climate pattern or event in our lifetime is somehow the result of enhanced GHG concentrations requires ~~one to restrict the climate system's wide capabilities in order to conclude~~ the assumption that natural variations are insignificant. This is especially true for precipitation events. With this caveat in mind we ~~will~~ examine the evidence for changes in weather and climate extremes.

Extremes in daily temperatures in the Conterminous US (CONUS)

~~Available to us are~~ Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available, beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (Quinlan et al. 1987, Karl et al. 1990). These

stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although errors certainly reside in the dataset, with over 1,000 stations any underlying signal we discover should can be characterized by relatively high confidence.

Daily record extremes in TMax and TMin

Has the occurrence of daily record high or low temperatures changed since Dec 1898? Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar, includes 29 Feb). For each of these days and each of the stations we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, we would expect, on average, that a station would experience an average each year of 1.21 records for TMax and 0.96 records for TMin records for TMax (TMin). Figure X indicates the distribution in time of the occurrence of these extreme events.

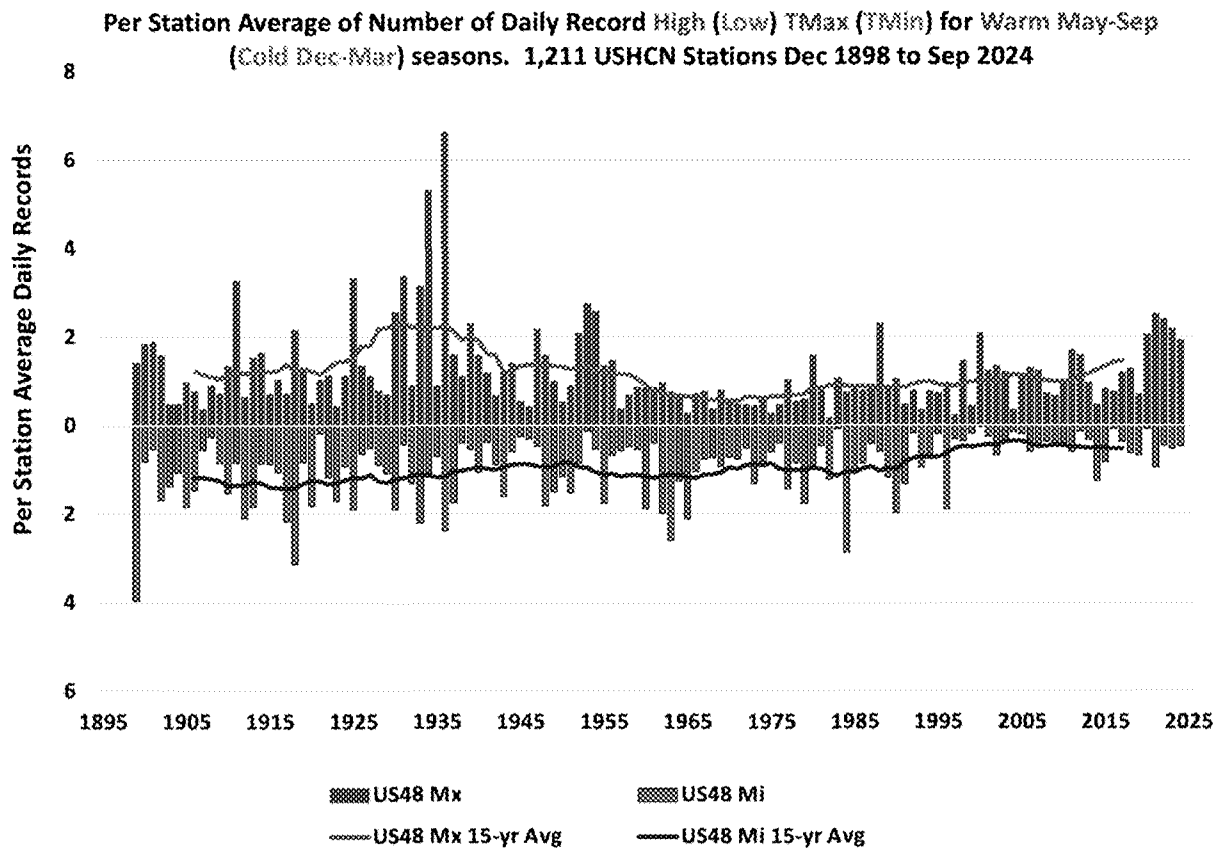


Figure X. Per station average of number of daily record High (red) and Low (blue) for warm and cold seasons in the CONUS. The lines represent 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

The results indicate a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s. On the cold side ~~other extreme~~, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 2nd. Overall, the number of cold records has declined, especially over the past 25 years.

Heat Threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent US National Climate Assessment report (NCA5) notes the increase in a threshold metric of number of days at or above 95°F, stating,

“The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US.”

Is the occurrence of 95°F days changing? As a non-parametric statistical variable, a threshold statistic can be misleading. A region with many stations which have near 95°F TMax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not impact the results much at all. In the past 126 years, the average CONUS station experienced 129 days per 6-yr period, but the regional values range from 249 in the Pacific Southwest to 9 in the Northeast. Thus, one needs to view such threshold analyses with caution.

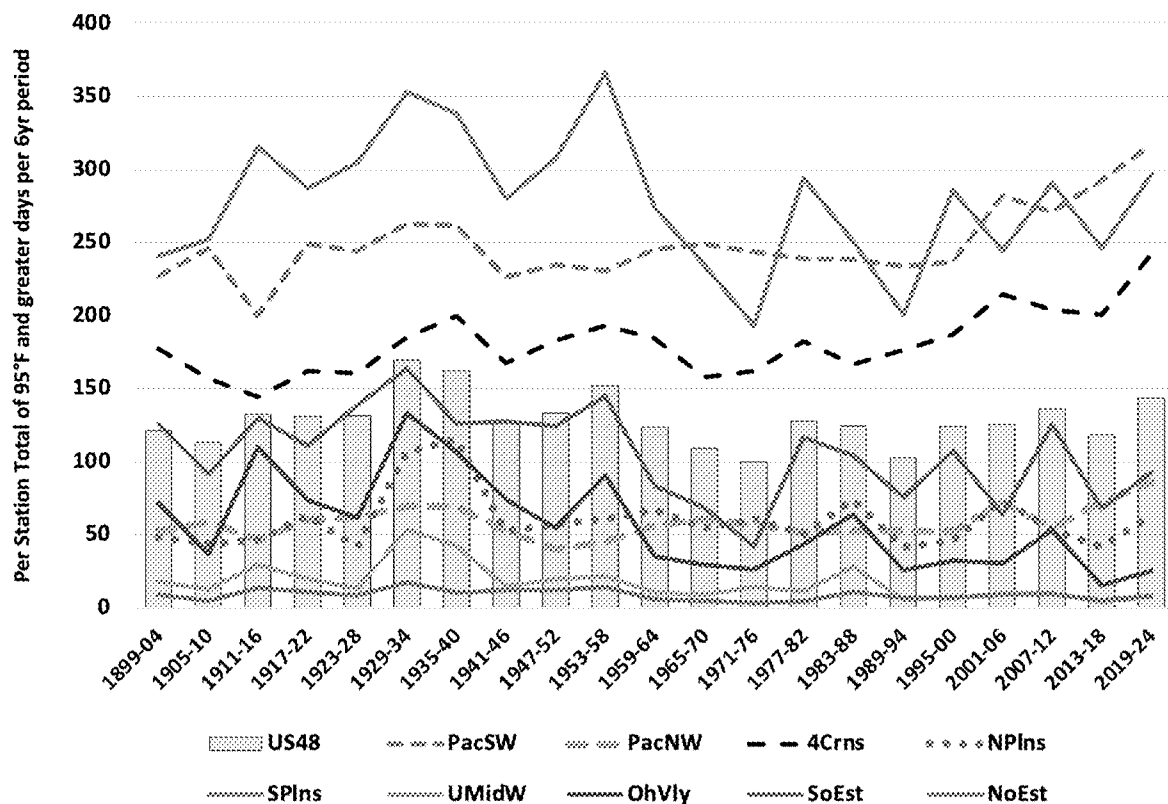


Figure X. Per station average of total number of days > 94°F in 6-yr periods.

In Fig. X we see that only three of the nine regions, all in the West, have experienced upward trends for 95°F or hotter days. The entire CONUS and the other six regions have experienced declines. The Heading “The Risk of Temperature Extremes is Changing” suggests positive trends are now being observed, but that is not evidenced in the combined results of Fig. X. That the “Risk” is changing can thus be applied only to forecasts which is addressed in section XX

Heatwaves

Of more impact than a single daily record is the phenomena of heatwaves, or consecutive days which exceed an extreme threshold. For this study, the metric will be the number of “Heatwave Days” defined as the sum of all days in May-Sep each year which exceed the 90th percentile on

consecutive days of at least seven days in length. IS 7 the conventional length? We use 3 days in our weather forecasting

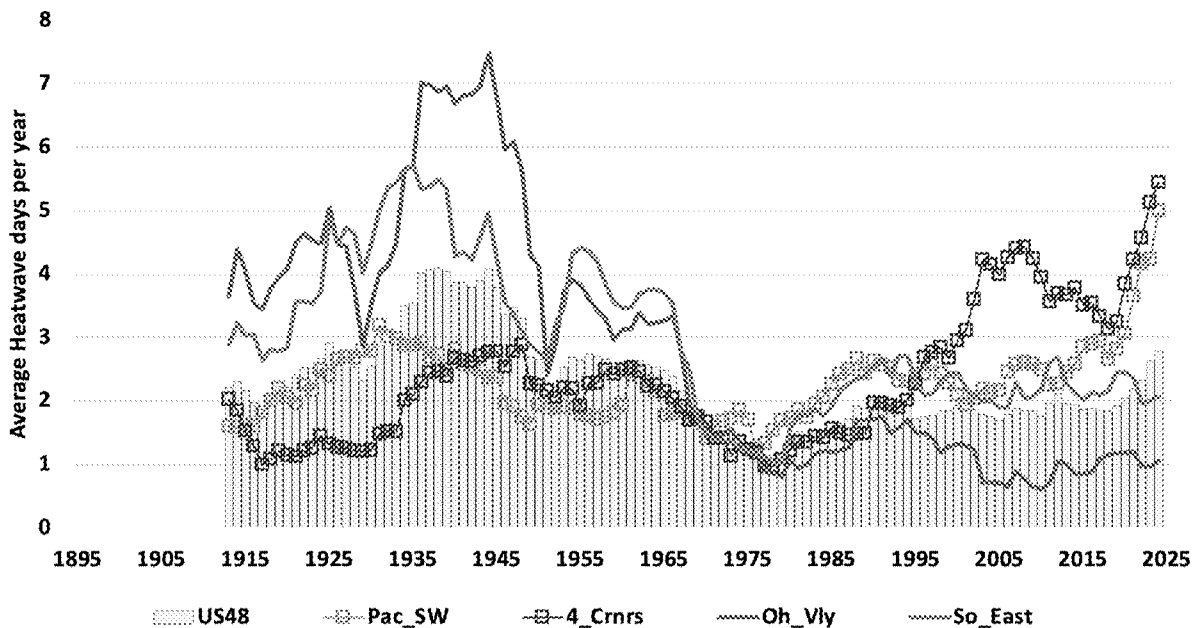


Figure X 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (orange squares, CA, NV), 4_Crnrs (red squares, AZ,NM,UT,CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure X indicates again the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, as seen in the sub-regional values for the Ohio Valley and the Southeast as examples. The West has seen a recent increase of heatwave days and the two sub-regions with the highest number are shown, the Pacific Southwest and the Four-Corners (NCA5). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West.

Regarding a different heatwave metric, NCA5 directs readers to the website

<https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view the number of urban heatwaves by decade from the 1960s. The figure reveals a monotonic increase in each

decade from 2 in the 1960s to 6 by the 2020s. The definition of a heatwave is unusual here - a period of at least 2 consecutive days when the apparent minimum temperature (combination of temperature and humidity) exceeds the 85th percentile. More importantly, the dataset is limited to the 50 largest cities in the US.

These results presented in USGCRP (2023) are entirely reasonable, but for reasons unrelated to GHG emissions. Urbanization in these cities is a major factor in the rise of TMin relative to TMax and to TMin at rural stations. Also, the decades of the 1960s and 1970s were the two coldest decades since the 1910's, so the starting date preconditions the time series to show warming. This does not dismiss the real rise in nighttime temperatures in major US cities and the impacts associated with these changes. However, we note for a variety of reasons, that summer TMax (especially in rural areas) serves as better response variable for detecting potential changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs – our concern in this document (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves in the CONUS.

Range of extremes

In the metrics above and other heat indices, a common feature emerges in which the range of CONUS temperature extremes has experienced a decline in the last 126 years.

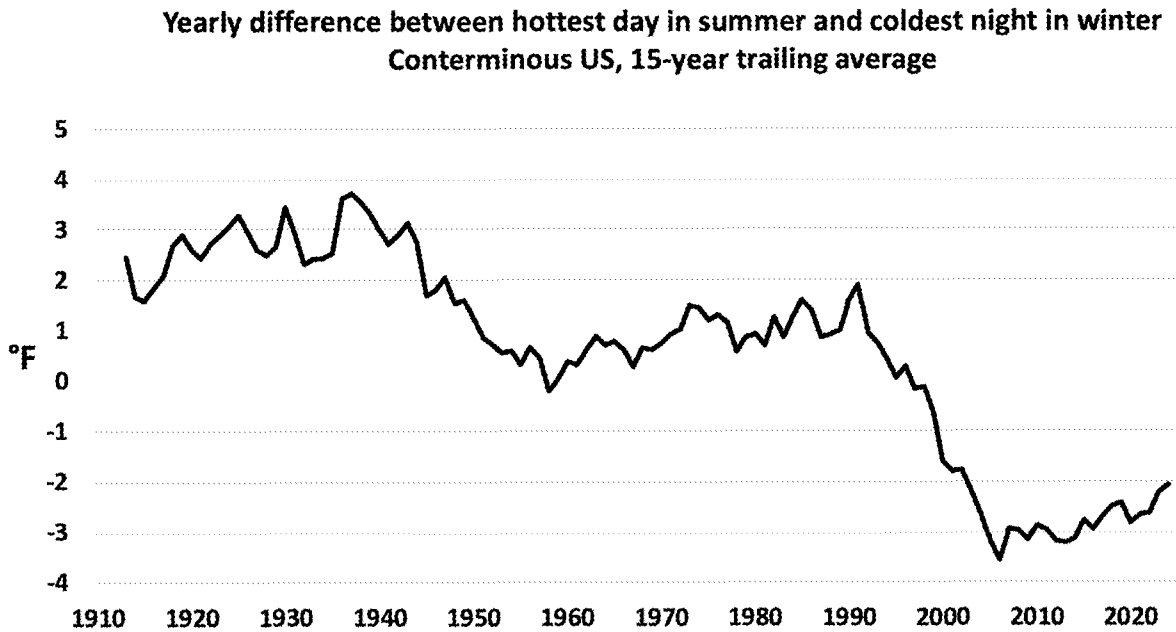


Figure X. 15-year trailing average of the difference each year of each station's hottest warm-season TMax and coldest cold-season TMin relative to the long-term average.

Figure X shows that the average difference for each station between the hottest summer TMax and coldest winter TMin has declined about 5°F in the past 126 years. The decline is due mostly to warming winter TMin, but a decline in the magnitude of summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (Spencer et al. 2025).

The information from these (and other analyses) indicates that any change in daily temperature extremes is difficult to ascribe to enhanced GHG concentrations.

I COVER THIS CASE IN THE ATTRIBUTION CHAPTER, CH 6 I think. I WOULD MOVE SOME OF THIS TO CHAPTER 6 and NOT INCLUDE HERE???

A Sidebar? – PacNW Heat Wave

Under the heading “The Risk of Temperature Extremes is Changing” the NCA5 states: “Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021.”

Firstly, the statement that several heatwaves have occurred in the US since 2018 is not evidence in support of the statement that the “Risk” of these events is changing, unless the change NCA5 is suggesting is that we will see fewer heatwave events in the future since there has been an observed decline over the past 126 years (Fig X).

Does the June 2021 Heatwave support the claim that the “Risk” is changing? The 2021 event in the Pacific Northwest was indeed significant, being accompanied by temperatures well-above previous “all-time” (i.e., in the last ~125 years) records. Early claims stated the event was decidedly influenced by GHG concentrations and was a sign of things to come (e.g., Philip et al. 2022) though others were more cautious (e.g., Overland 2021, Thompson et al. 2022, White et al. 2023).

Mass et al. 2024 performed a detailed analysis of the event and demonstrated that this was truly a “Black Swan”, or an extremely rare event, outside of the range of the small historical sample available to researchers (1895-2021). Their final remark was “Global warming may have made a small contribution, but an extreme heatwave, driven by natural variability, would have occurred in any case.

The event’s remarkable nature, magnitude and rarity are indicated by the fact the deep tropospheric temperature anomaly in the Pacific Northwest for the pentad dated 25-29 June 2021 was +11 °C, representing the hottest single summer NH grid point anomaly in the 46-year satellite record which contains over 4 million values. In terms of “all time” record high surface temperatures,

over 60% of stations in WA and OR achieved theirs in 2021. However, with the removal of this single event, the time series of “all time” record TMax’s in WA and OR shows a decline since 1911, suggesting there is no pattern of increasing hot extremes. As to model projections of heat waves in the Pacific NW, Mass et al. state, “projected circulation changes associated with global warming show no evidence of amplifying the synoptic features associated with Pacific Northwest heatwaves.” These results suggest the heatwave of 2021 does not readily support evidence of a change in the Risk of extreme temperature events.

Extremes in daily precipitation.

Due to its stochastic and episodic character, precipitation requires careful statistical treatment to understand variability over long time periods. Of concern in this report is the reasonable assumption that warmer air has a greater capacity to hold moisture and thus if the atmosphere warms (a GHG response), this which could lead to extreme events of greater frequency and/or magnitude. ~~In addition, precipitation processes are more efficient as the environmental air warms, potentially increasing the rain rates as well.~~ NOT NECESSARILY TRUE. COLD RAIN PROCESSES INVOLVING ICE CRYSTALS ARE MORE EFFICIENT; LOWER EFFICIENCY OF COLD RAIN PROCESSES IF TEMP WARMS

The US National Climate Assessments (NCA4, NCA5) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme events are in the Northeast and least in the West, which is counter to the changes in temperature extremes shown above.

McKittrick and Christy 2019 examined long-term and consistent station observations of daily precipitation to test some of these NCA claims for the Southeast and West Coast. In neither

case when the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978) were the trends significant. We update these findings with similarly constructed observations from 29 stations on the Pacific Coast (1893ff from San Diego CA to Blaine WA), 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), and 21 stations in the Northeast (1888ff from Buffalo NY to Portland ME – the region where trends are greatest).

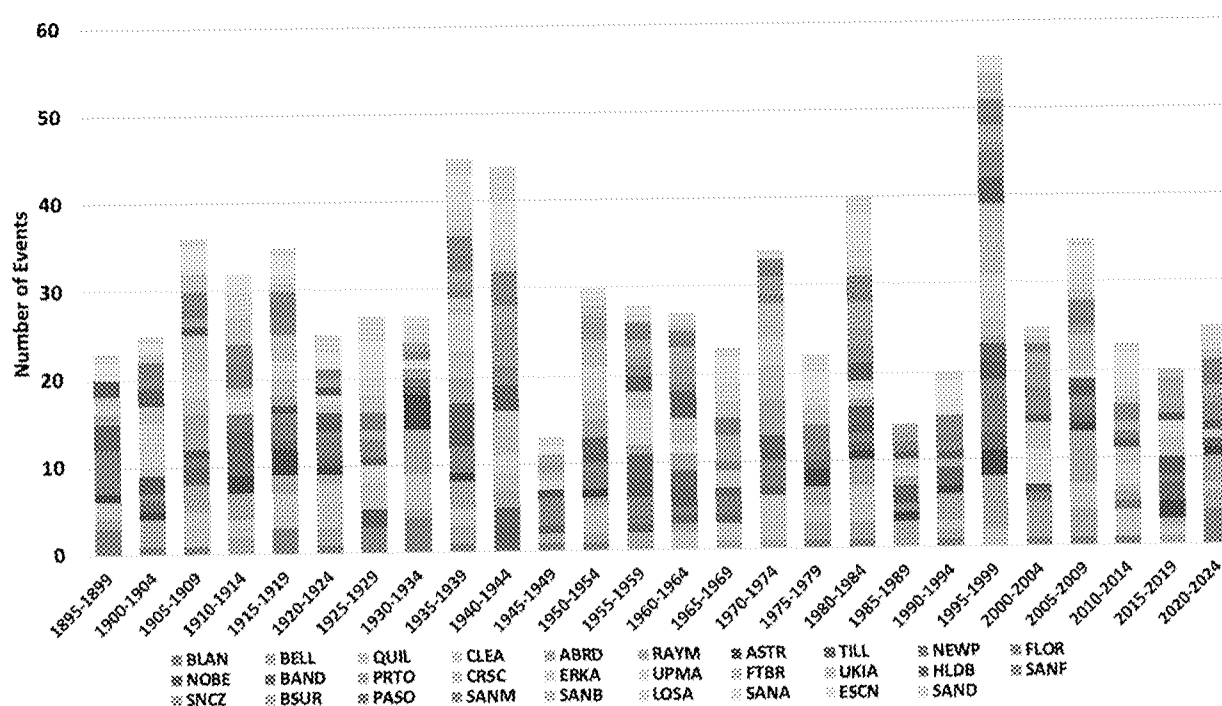


Figure X. The time distribution by 5-year periods of the 26 heaviest occurrences for each station (i.e., nominal 1-in-5 year event). I FIND THIS DIAGRAM VERY DIFFIULT TO INTERPRET, EVEN THE STATION NAMES

The Pacific Coast receives considerable amounts of precipitation in from Atmospheric River (AR) events which often last more than a day or two. In Fig. X we show the distribution in time of the 26 heaviest 5-dy precipitation totals (nominal 1-in-5yr occurrence). The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of these types of precipitation metrics, there is no indication of a tendency to change over time.

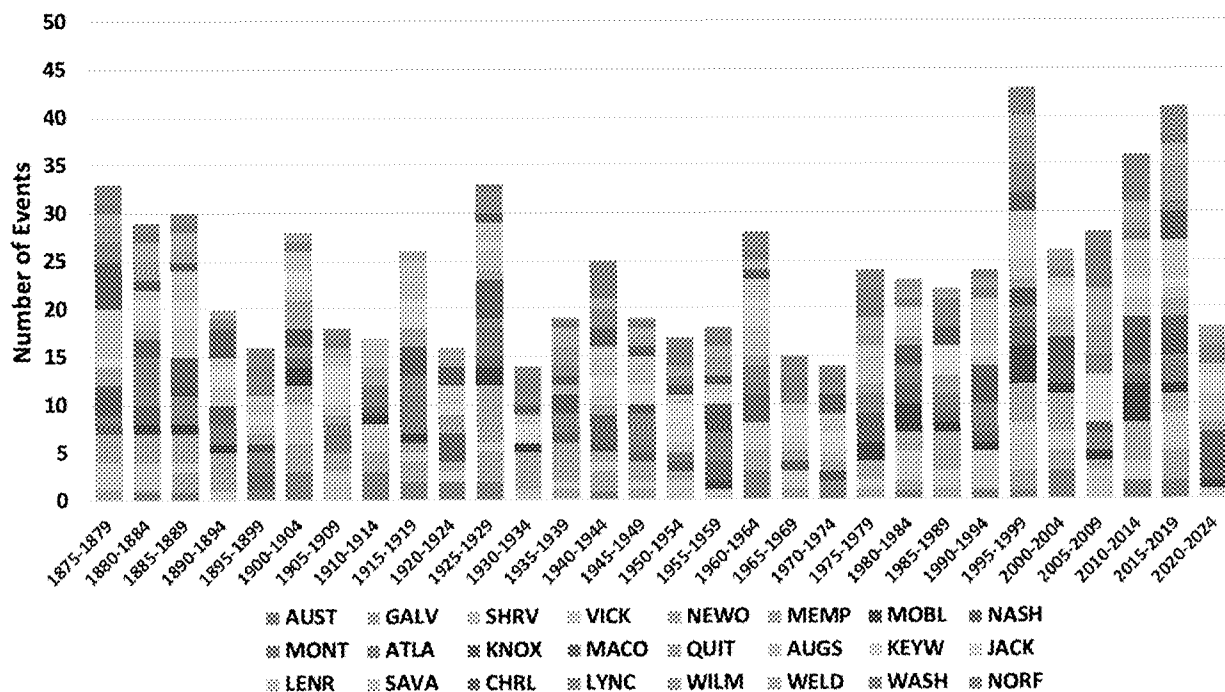


Figure X. As above but for the 30 heaviest 1-in-5yr events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2025.

INCLUDE THE HUGE AR from 1861/1862 I THINK THIS IS WORTH A MENTION

The event is similar to the exceptionally intense California storms that occurred between December 1861 and January 1862, which dumped nearly 10 feet of rain in parts of California

and submerged the entire Central Valley under as much as 15 feet of water.^{67,68} Six megastorms more severe than 1861–1862 have occurred in California during the last 1800 years, occurring at intervals of 200 years or so.⁶⁹

1 William Brewer, *Up and Down California in 1860–1864 The Journal of William H. Brewer* (Berkeley, CA: University of California Press, 1930).

2 Keith Porter et al., *Overview of the Arkstorm Scenario* (Reston, VA: Dept. of the Interior, U.S. Geological Survey, 2011).

3 Jan Null and Joelle Hulbert, “California Washed Away: The Great Flood of 1862,” *Weatherwise* 60, no. 1 (2007): 26–30, <https://doi.org/10.3200/wevi.60.1.26-30>.

The temporal pattern of 5-day totals of the 1-in-5yr heavy events in the humid Southeast is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and

NCA5 of a tendency for an increasing frequency of heavy events, due to a temporal clustering of tropical storms, from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

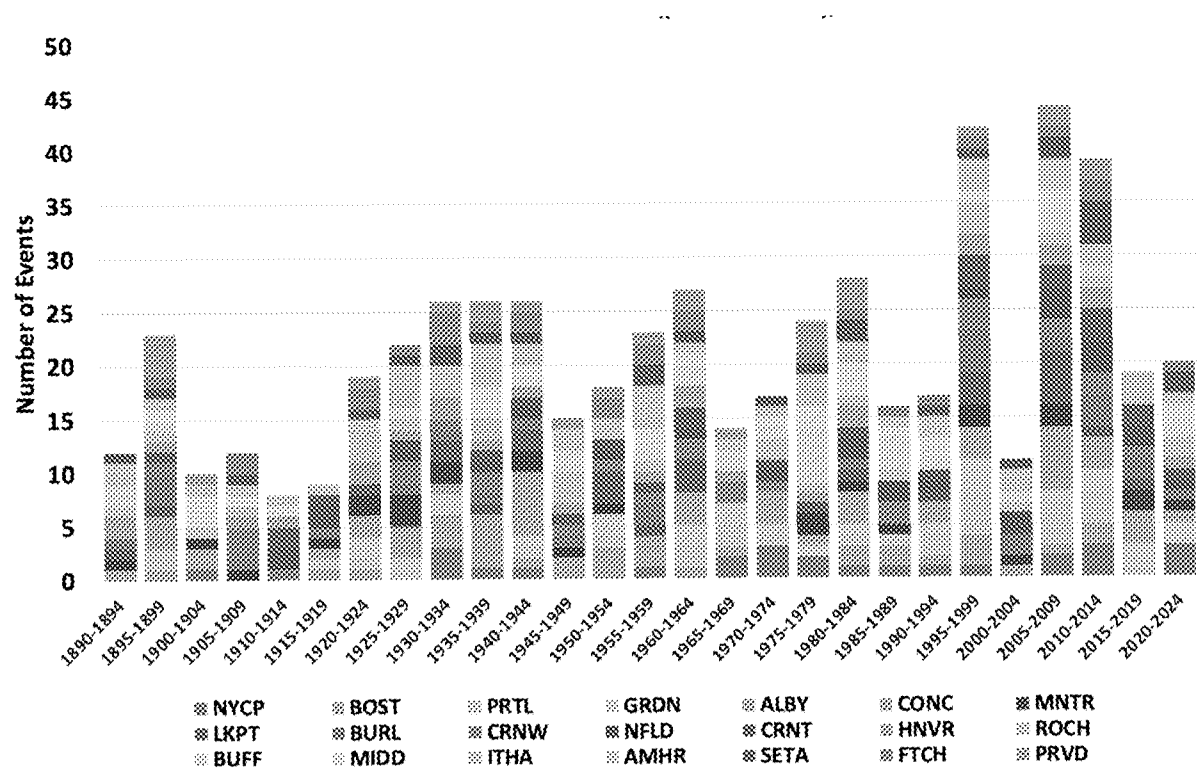


Figure X. Time distribution of the heaviest 27 (1-in-5yr) heaviest 3-day precipitation events for 21 stations from NY to ME, including Montreal. AGAIN I FIND INTERPRETING THIS FIGURE VERY DIFFICULT

In Fig. X is displayed the 27 (1-in-5yr) heaviest 3-day events for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest variations in time. In this region, 72% of the events occur during June to October and are dominated by tropical incursions of hurricanes, tropical storms or tropical storms that transition to extratropical systems.

Howarth et al. 2019 report differences in the Northeast between two 18-year periods: 1979-96 and 1997-2014 (a similar region as in Fig. XX that includes PA and NJ) of various precipitation extremes, one of which indicated a dramatic increase (317%) in the 24-hr events > 6 inches. This high increase is due to the very small numbers of such events of which there were only 6 in the first period and 25 in the second. Most of the stations did not record such an event suggesting these erratic, episodic events over brief, 18-yr periods, need scrutiny by additional statistical methods.

Using the information in Fig. X over the same years as Howarth et al. we find an increase of the frequency of heavy events between the two periods of 51%. One can see in Fig. X that it was unfortunate that Howarth et al. ended in 2014 prior to a return to the long-term average of such events.

A feature of Howarth et al. is the use of single day totals which is questionable because extreme events are often spread across the observation time boundary, so that stations measuring at 0700 LT versus those at Midnight will have differing results and which would then have major impacts on counting rare events. We use the 3-day totals in Fig. X to be sure to capture the extent of these short events. In any case, we can confirm that the period 1997 to 2014 provided a cluster of heavier events as Howarth et al. have documented.

Howarth's most remarkable claim (317% increase in 6" days) is potentially misleading because it is a threshold statistic (see above under Heat Threshold) and a ratio of small numbers over a short period. The result is not representative of *relative* extreme events for the whole region since the majority of stations never experienced a 6" total. Fig. X above determines the same number of events for each station (27 heaviest events) whose heaviest events ranged from 4.4" to 12.5" and 27th heaviest event ranged from 3.3" to 5.0". This analysis thus normalizes the extremes so each station is equally represented. Note too that the period of record here is 135 years vs. 36 years of Howarth et al. Except for three 5-year periods between 1995 and 2014 there is nothing statistically remarkable about the results.

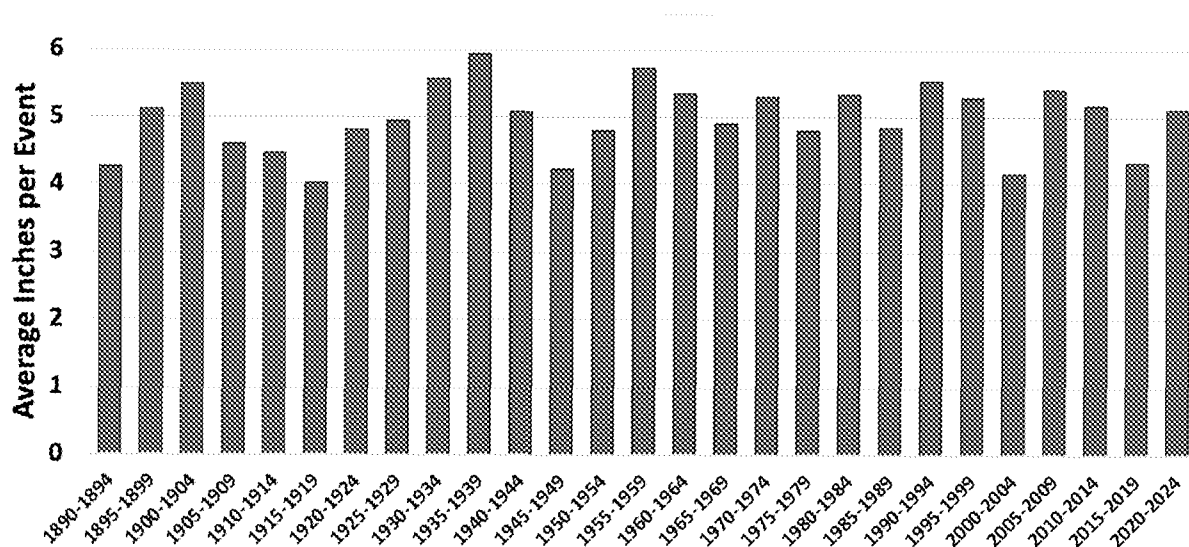


Figure X. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

An interesting aspect of Northeast precipitation is that there has been no change in the amount of precipitation per heaviest event as seen in Fig. X (a minuscule trend of $+0.02''/\text{decade}$). This result suggests that though there was an uptick in the number of events during the period 1995 to 2014; the events, individually, are not becoming more intense.

Jong et al. 2024 document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, “The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s.” The question then becomes, was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. X where the amount-per-event has remained steady over the 135-year period.

The evidence from the historical record of extreme precipitation events is generally not consistent from region to region so that inferences regarding trends and their projections are

wrought with significant uncertainty. In most regions and perhaps all, it is our opinion that the very nature of the erratic and episodic character of extreme precipitation events renders the discovery of statistically significant changes a result yet to be achieved (McKittrick and Christy 2019).

URBAN HEAT ISLAND IS ALSO A FACTOR IN RAINFALL EXTREMES, MAYBE SOMETHING ABOUT THIS

ADD SUMMARY SECTION WITH MAIN CONCLUSIONS

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The carbon cycle and CO₂ emission scenarios

In addition to the uncertain sensitivity of the climate system to increasing CO₂, future climate projections also depend upon uncertain estimates of how much “extra” CO₂ will accumulate in the atmosphere in the future. These uncertain estimates are a function of two components: (1) future rates of global anthropogenic CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere.

Global carbon cycle and local emissions policy

Global carbon cycle models are used to quantify the second component, using estimates of various land and ocean processes that remove CO₂ from, and emit CO₂ into, the atmosphere. Our understanding of these processes was reviewed by Crisp et al. (2021). The natural fluxes of CO₂ in and out of the Earth’s surface are very large, many times anthropogenic emissions, but those CO₂ sources and sinks were assumed to be in approximate balance in pre-Industrial times, as evidenced by relatively constant levels of atmospheric CO₂ in centuries past derived from air bubbles in ice cores. This is one of the reasons why increasing atmospheric CO₂ levels are believed to be dominated by anthropogenic sources.

Specifically, fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) has led to steadily increasing CO₂ levels in the atmosphere, as shown in Fig.1.4.3.1.

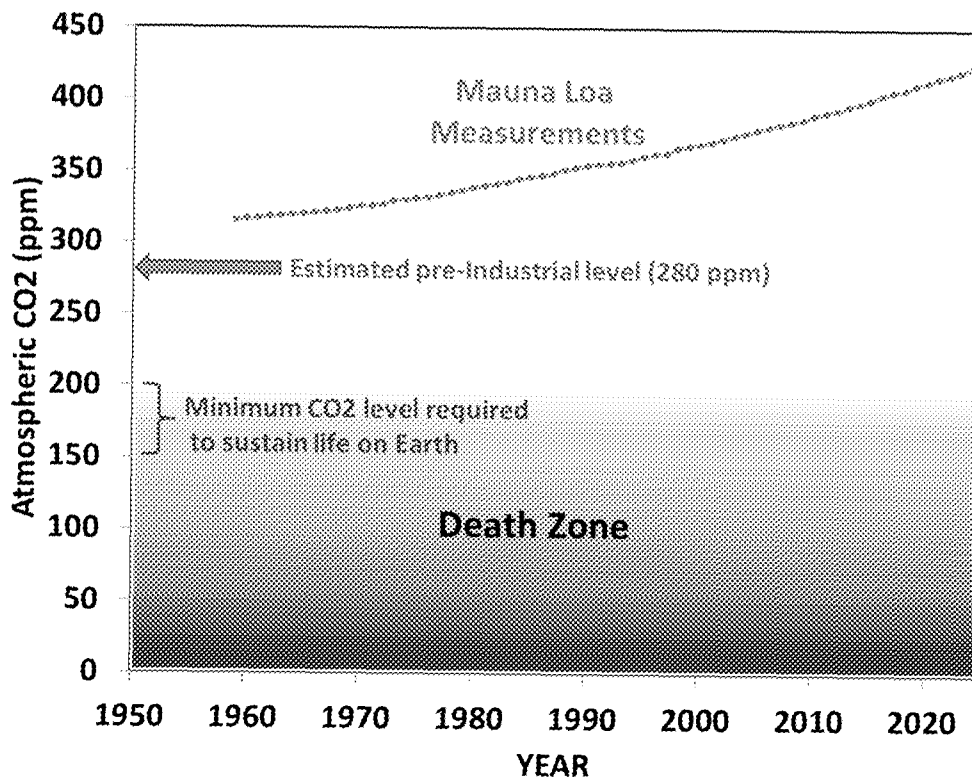


Fig. 1.4.3.1. Yearly average atmospheric CO₂ concentrations (1959-2024) measured at Mauna Loa, HI (green) compared to the estimated pre-Industrial CO₂ concentration of 280 ppm, and the estimated minimum levels required to sustain life on Earth (150 to 200 ppm). **NEED SOURCE**

As noted in Fig. X1, life on Earth requires CO₂ levels of at least 150 to 200 ppm. This is because the food chains on land and in the ocean begin with vegetation and biota that depend upon photosynthesis, which requires CO₂.

CO₂ emissions from fossil fuel burning is a small component of the natural carbon cycle. About 44,000 Gigatonnes of carbon-equivalent (GtC) are stored in the atmosphere and oceans, mostly in the form of CO₂. (Ciais et al. 2013). Between 150 and 200 GtC are released naturally each year through oceanic outgassing and land-based processes like plant decay and animal respiration. A variable but roughly equivalent amount is absorbed each year by the land and oceans, with a small net loss from the atmosphere because the formation of deep ocean sediment sequesters some carbon permanently. Global fossil fuel consumption and cement manufacture released about 10.3 GtC in 2023, up from 6.2 GtC in 1990 (Ritchie et al. 2024). Of this, about half is naturally sequestered through plant growth and oceanic uptake while the remainder, about half, adds to the atmospheric stock (Ciais et al. 2013).

The policy issues related to CO₂ are fundamentally different from those related to criterion air contaminants like SO₂ and NO_x for two reasons. First, in the case of criterion air contaminants we are concerned with the local ground-level concentration, since that is what affects human welfare. But local variations in CO₂ levels do not affect human health, the potential channel of influence is through variations in the global climate which operates through the global average atmospheric CO₂ concentration. (Another influence is the positive local effect on crop productivity which will be discussed in Section 3.2). Second, policy can only change the flow of emissions, not the stock, and with criterion air contaminants the two are closely connected because the stock is relatively small. When emissions are reduced the local pollution concentration drops rapidly, usually on a time scale of a few days. Not so with the global average CO₂ concentration since global carbon cycle is vast and slow. A change in local emissions today will only have a very small global effect, and only after a long time lag. After a pulse (release) of CO₂ emissions to the atmosphere only about 40 percent ($\pm 15\%$) of the emitted molecules will have been sequestered after twenty years. After a thousand years about 75 percent ($\pm 10\%$) will have been sequestered, and the remainder will gradually be removed over the ensuing tens of thousands of years (Ciais et al. 2013, pp. 472-473). Consequently US CO₂ emission reductions will take decades or centuries to lead to a reduction in the global CO₂ concentration.

The CO₂ level as recorded at the Mauna Loa observatory in Hawaii is generally used as the representative global average concentration. The data are available online at <https://gml.noaa.gov/ccgg/trends/index.html>. The concentration was about 316 ppm at the start of the record in 1959 and is now about 425 ppm, a 34 percent increase. The record exhibits monthly fluctuations of about 0.5—2.0 ppm due to plant growth and decay, superimposed on an upward trend that averages 1.7 ppm per year. To reduce the atmospheric stock of CO₂, assuming the entire increase is anthropogenic, would require emissions to fall below the natural sequestration rate. The 1997 Kyoto Protocol proposed to cap industrial nations' CO₂ emissions at five percent below 1990 levels by the year 2012. Even though this policy ended up too costly for most nations to implement, full compliance would not have reduced atmospheric CO₂ levels. They would only have slowed down slightly slowly, reaching

their projected 2100 level in 2105 instead (Wigley 1998). Similarly Lomborg (2016) used the well-known MAGICC climate model and showed that full compliance with the Paris Accord would delay hitting the baseline year 2100 levels about a decade later instead.

Thus, in contrast with conventional air pollution control, local actions yield extremely small local effects, and only after a long time lag. The practice of referring to unilateral US reductions as “combatting climate change” or “taking action on climate” reflects a profound misunderstanding of the scale of the issue.

Sequestration of CO₂

As noted, each year natural processes remove a net amount of CO₂ equivalent to about 50% of global emissions. Thus, anthropogenic CO₂ emissions average twice what is required to explain the atmospheric rise in CO₂ concentration. The near-constancy of that 50% fraction also means that the more CO₂ humanity produces, the faster Nature removes it from the atmosphere. That 50% fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Nino, La Nina, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert et al., 2004).

The main processes which remove excess CO₂ from the atmosphere are increased production of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein et al., 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon observed by satellites since monitoring of global greenness began in the 1982. This greening has been traced to CO₂ fertilization and greater drought tolerance of plants exposed to elevated CO₂ levels. While there had been some uncertainty whether a greening trend continued beyond 2000, the most recent research (Chen et al., 2023) has shown continued greening, with even some slight acceleration since 2000. Global greening is discussed further in Section 3.1.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be reliably measured. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp et al. (2021).

When the two components required to estimate future atmospheric CO₂ concentrations are combined (anthropogenic emissions estimates along with carbon cycle model estimates of atmospheric CO₂ removal), we get estimates of future CO₂ concentrations required by climate models to estimate future rates of warming.

IPCC Emission scenarios have long been biased upwards

For the IPCC 3rd and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* were used, and hence were referred to as the SREP scenarios. McKittrick et al. (2012) showed that, when converted to per capita terms, the SREP scenario distribution was skewed upwards

and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by analysis in Hausfather et al. (2019) who showed that observed atmospheric CO₂ levels tracked the lowest of the SRES forecast range.

For the Fifth Assessment Report the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCP). Each RCP is identified by a number representing the increase in warming forcing in Watts per square meter over the 21st century resulting from GHG emissions. The RCP scenarios are thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying a gain of 2.6 Watts per square meter) projects a GHG concentration pathway which implies warming remains well below 2°C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5°C warming just in this century.

In both the academic literature and popular media RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario. It was used in this way to generate the reference outcome supposedly representing the 21st century world in the absence of emission reduction policies. But RCP8.5 was in fact an extreme high emissions scenario and its usage as a baseline has been grossly misleading. Hausfather and Peters (2020) writing in a commentary in *Nature* magazine, pointed out that RCP8.5 was developed as an extreme worst case scenario, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting:

RCP8.5 was intended to explore an unlikely high-risk future. But it has been widely used by some experts, policymakers and the media as something else entirely: as a likely ‘business as usual’ outcome. A sizeable portion of the literature on climate impacts refers to RCP8.5 as business as usual, implying that it is probable in the absence of stringent climate mitigation. The media then often amplifies this message, sometimes without communicating the nuances. This results in further confusion regarding probable emissions outcomes, because many climate researchers are not familiar with the details of these scenarios in the energy-modelling literature.

(Hausfather and Peters 2020)

The implausibility of the RCP8.5 scenario was examined by Burgess et al. (2021). They noted that RCP8.5 has already diverged from observed energy use trends, and the near future trends diverge sharply from those of the International Energy Agency (IEA) which provides market-based projections of energy use for coming decades. IEA trends are based on plausible extrapolations of current economic and demographic trends, and the results run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but even lower emission scenarios are looking unlikely. Burgess et al. comment (p. 8):

Beyond 2040, if the trends anticipated by energy agency forecasts continue, carbon intensity will continue diverging from AR5 and SSP baselines—especially from higher-emission scenarios such as RCP8.5, due to the assumptions about fossil-fuel expansion in these scenarios that are increasingly implausible.

The problem of bias towards alarmism in the climate impacts literature fueled by implausible extreme high emission scenarios was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They

found (p. 32) that between 2010 and 2020 some 16,800 scientific papers had been published using the RCP8.5 scenario, and (p. 16) that about 4,500 of the articles linked RCP8.5 with the concept of “business-as-usual”. They provided analyses of how RCP8.5 was misused not only by individual researchers, but by influential science agencies like the IPCC and the US National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets. They provide the following example (p. 30):

The USNCA employed RCP8.5 as a baseline scenario, despite warning against such use, and compared it to RCP4.5 throughout its report to generate quantitative economic estimates of the benefits of mitigation. In a front page story, the *New York Times* promoted the report’s misuse of RCP8.5 as a baseline scenario:

“A major scientific report issued by 13 federal agencies on Friday presents the starkest warnings to date of the consequences of climate change for the United States, predicting that if significant steps are not taken to rein in global warming, the damage will knock as much as 10 percent off the size of the American economy by century’s end.”

Pielke and Ritchie (2020) reported new studies using RCP8.5 were appearing in the literature at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and “business as usual.” They conclude (p. 34) that the climate research community has spent a decade “committing scientific resources to science fiction” (emphasis added):

“Derived estimates from RCP8.5 as “business as usual” such as future climate impacts, the impacts avoided from mitigation and the cost effectiveness and benefits of mitigation have no real-world meaning... **The scientific literature has become imbalanced in an apocalyptic direction.**

(Pielke Jr. and Ritchie p. 34)

The IPCC later modified the RCP scenarios to the “Shared Socioeconomic Pathway” or SSP scenarios, but these have continued the pattern of bias shown with the RCP and SRES scenarios. Figure 1.4.3.2, generated using the Resources for the Future Global Energy Outlook tool (RFF 2025).

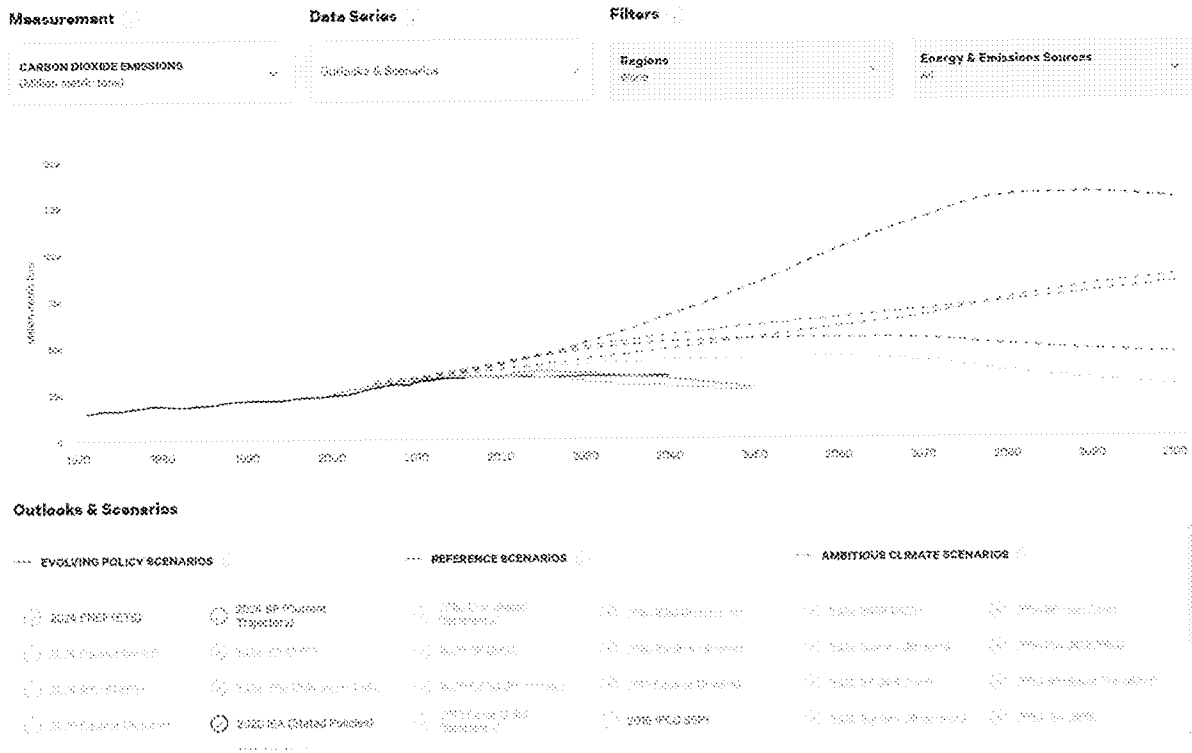


Figure 1.4.3.1. Observed and projected CO₂ emissions. Source: RFF (2025).

Because the largest uncertainty lies in future global rate of anthropogenic CO₂ emissions, the IPCC has used a wide variety of possible emissions scenarios, and the four most common ones from the CMIP6 climate model experiments are shown in Fig. X2.

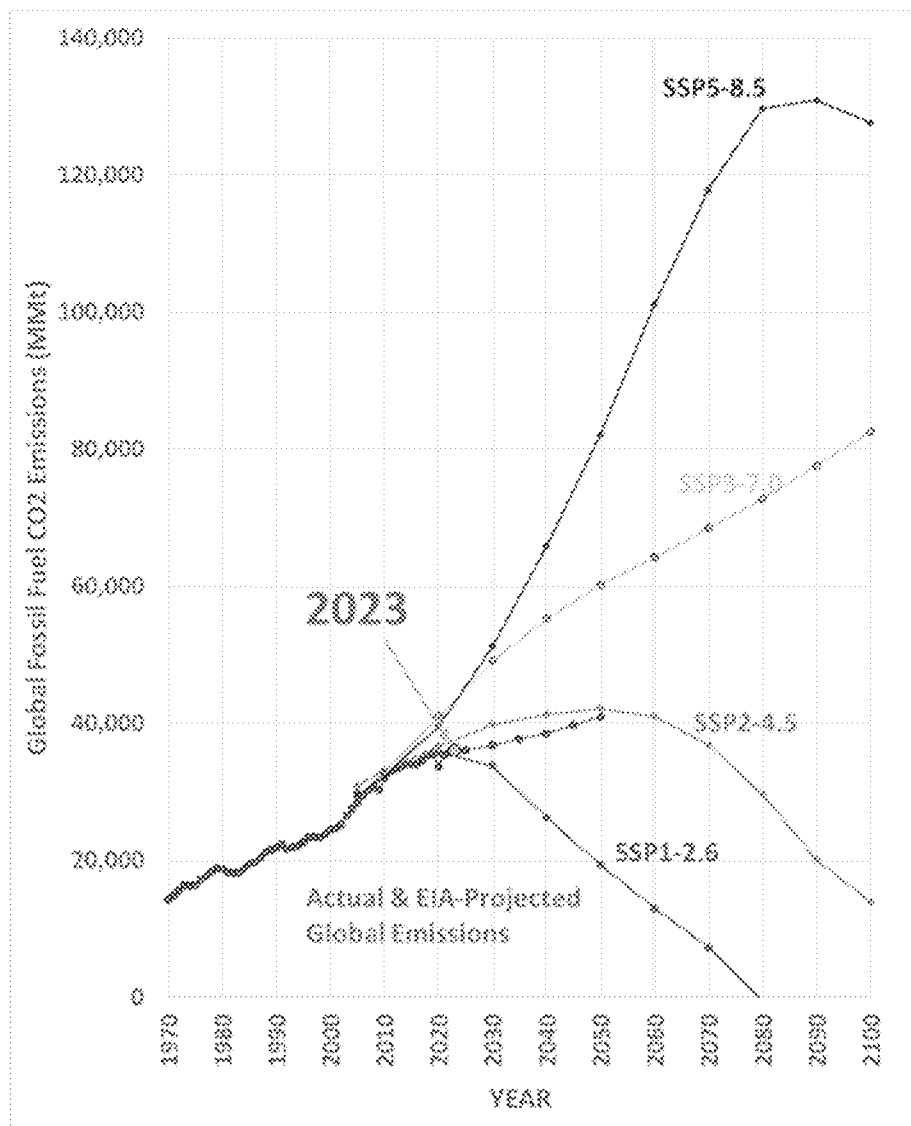


Fig. X2. The Shared Socioeconomic Pathway (SSP) scenarios of future atmospheric CO2 concentrations used by the IPCC in their CMIP6 climate model projections, compared to actual global emissions (up to 2023) and EIA-projected emissions, 2025-2050 (green). **Need source**

Also shown in Fig. X2 are the yearly estimates of past global CO2 emissions (green) along with Energy Information Administration (EIA) future estimates based upon projections in global energy use every five years until 2050.

Importantly, as of 2023 global CO2 emissions have been tracking *well below* the two highest emissions scenarios used by the IPCC (SSP5-8.5 and SSP3-7.0). This is significant because most of the climate model projections relied upon for energy policy decisions have been from these two emissions scenarios (or

similar scenarios), which are now increasingly considered unrealistic (e.g. Ritchie and Dowlatabadi, 2017; Pielke & Ritchie, 2017; Pielke & Ritchie, 2021).

Yet, despite these unrealistically high CO2 concentrations, extreme climate projections are still widely used by the IPCC, environmental groups, and in reports (e.g. the Fifth U.S. National Climate Assessment, NCA5) to warn of the dangers of climate change. In other words, the public and policymakers are being misled by climate model projections showing *what could theoretically happen if CO2 emissions increase drastically, even though recent trends indicate that will not happen*. This is one more reason why current climate model projections, and especially assessments which only highlight unrealistic future emissions scenarios, should not be relied upon for energy policy decisions.

As shown above, there is also increasing evidence for benefits to life on Earth from more CO2 in the atmosphere.

1.1 Estimates of the Social Cost of Carbon [RM]

Text text text.

3. Increasing CO₂ and the Alkaline Oceans

The modern-day global average pH of sea water is estimated to be 8.1, down from an estimated value of 8.2 in pre-Industrial times (Gattuso and Hansson, 2011). As CO₂ concentrations in the atmosphere increase, more is absorbed by the oceans. Depending upon the alkalinity (buffering capacity) of the oceans, the oceans are expected to become somewhat less alkaline over time, putatively explaining the decrease in pH from 8.2 to 8.1 over the last few hundred years.

While this process is often called “ocean acidification”, this is a misnomer because the oceans are not expected to become acidic (pH less than 7.0). Even if that was to happen, it is believed that life in the oceans evolved during a period when the oceans were mildly acidic, with a pH of 6.5 to 7.0 (Krissansen-Totton et al., 2018).

For many years it was assumed that a decreasing pH of sea water would reduce the calcification rate of coral reefs. But coral reefs already endure large swings in pH, partly due to daily photosynthetic activity in the reef. This results in pH values that have been measured to range from 9.4 during the day to 7.5 at night (Revelle and Fairbridge, 1957).

In 2009 it was reported that a portion of Australia’s Great Barrier Reef (GBR, the world’s largest coral reef ecosystem) had experienced a 14% decline in calcification since 1990 (De’ath et al., 2009). This was tentatively attributed to increasing water temperature and decreasing pH of seawater. But since that time, the initial 2009 report of reduced calcification rates in the GBR was reported to have been the result of a bias in the data analysis (Ridd et al., 2013), and correction for this bias led to no change in calculated calcification rates. Nevertheless, the alarm produced by the original paper has persisted as evidenced by the large number of published citations (541) received by the original study as compared to only 11 citations for the subsequent study (as of 30 April 2025).

Given the reported declines in GBR coverage between 1990 and 2009, it has come as a surprise that the decline reversed over the last decade or so, with Woods Hole Oceanographic Institution asking, “*Is the Great Barrier Reef Making a Comeback?*” (Woods Hole, 2023). The most recent annual summary of GBR conditions from the Australian Institute of Marine Science was titled, *Continued Coral Recovery Leads to 36-year Highs across Two-Thirds of the Great Barrier Reef* (AIMS, 2022). Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden et al., 2015), and recovery of the reef from storm damage takes years.

On the time scale of thousands of years, boron isotope proxy measurements of pH show that ocean pH was around 7.4 or 7.5 during the last Ice Age (up to about 20,000 years ago) increasing to present-day values when the world warmed during deglaciation (Rae et al., 2018). Thus, there appears to be considerable resilience of ocean biota to natural long-term changes in ocean pH since marine organisms are exposed to wide ranges in pH anyway.

It is being increasingly recognized that publication bias (alarming ocean acidification results preferred by high-impact research publications) leads to exaggerated impacts from more alkaline oceans. An ICES Journal of Marine Science Special Issue addressed this problem with an article entitled, *Towards a Broader Perspective on Ocean Acidification Research*. In the Introduction to that Special Issue, H. I. Browman stated, “As is true across all of science, studies that report no effect of ocean acidification are typically more difficult to publish.” (Browman, 2016)

Similarly, a meta-analysis of the negative effects of ocean acidification on reef fishes found that initially dramatic conclusions published in the scientific literature were all but refuted upon subsequent analysis involving larger sample sizes of data (Clements et al., 2021).

In conclusion, it is becoming increasingly apparent that the effect of ocean “acidification” on marine biota has likely been exaggerated.

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Report of the Special Advisory Group on Carbon Dioxide and Climate Change

Submitted to the Secretary, US Department of Energy

May 30, 2025

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Table of Contents

Acronyms

Introduction

This document had its origin in an initiative undertaken in late March 2025 by Secretary Wright to assemble an independent team to write a brief report for him on issues in climate science relevant for energy policymaking, with particular focus on the question of whether carbon dioxide emissions pose a danger to the US public. The authors of this report agreed on the usefulness of such a document and agreed to undertake the work on the condition that there was to be no editorial oversight by the Secretary, the Department of Energy or any other government personnel. This condition has been honored throughout the process and the writing team has worked with full independence.

The team began working in early April with a final submission deadline of May 28. Because of the short timeline and the technical nature of the material we have not tried to produce a comprehensive review of all topics. While the report is intended to be accessible for non-experts, we deliberately omitted some introductory or explanatory material that can easily be accessed elsewhere. Nor have we attempted to survey entire literatures related to the topics selected for focus. The scientific and technical material herein is just a sample of the vast literature on climate change but is, we believe, more than sufficient to establish our conclusions.

The team writing this report was not involved in nor briefed on any administrative processes related to a potential challenge to the CO₂ Endangerment Finding. During the writing of this report we received no information about the Administration's plan on that matter. We were asked, however, to include some information related to the role of US motor vehicles in global climate change, since that is an issue of relevance to the Department of Energy.

The writing team wishes to express its thanks to Secretary Wright for the opportunity to prepare this report and for his support for independent scientific inquiry.

1 Carbon dioxide as distinct from criterion air contaminants

This report is chiefly concerned with carbon dioxide (CO₂) emissions from fossil fuel use. Although it has become common to refer to CO₂ as “pollution” this is a misnomer. In the framework of United States clean air policy there are six types of so-called Criterion Air Contaminants: particulate matter (PM), ground-level ozone (O₃), Sulfur Oxides (SO_x), Nitrogen Oxides (NO_x), volatile organic compounds (VOCs) and carbon monoxide (CO). Air contaminants are subject to regulatory control because they cause local problems depending on concentrations that include nuisances (odor, visibility problems), damage to plants and, at high enough exposure levels, toxicological effects in humans.

CO₂ has not historically been viewed as an air pollutant in the US or elsewhere because it is odorless, does not affect visibility and has no toxicological effects. It is a naturally-occurring part of the atmosphere and a key component of human and plant respiration. CO₂ is essential for plant photosynthesis and higher levels are generally considered beneficial for vegetation, as will be discussed in this report. There are no health consequences associated with elevated CO₂ levels except at concentrations many times beyond what the Earth now experiences or will experience under climate change. The main concern about CO₂ is its potential effects on the global climate. This is a very complex question which will occupy much of this report.

We will begin in the next section by looking at the role of CO₂ in promoting global greening and agricultural productivity growth. We then turn to CO₂'s role as a so-called greenhouse gas (GHG), beginning with a brief description of radiative forcing, the carbon cycle and the role of aerosols. Part II of this report discusses in detail the topic of the climatic response to GHGs. Part III discusses some aspects of the impacts of climate change on ecosystems and society.

Throughout this report we make use of information found in reports from the Intergovernmental Panel on Climate Change (IPCC), research from the peer-reviewed scientific literature and official data sources. In some places our summary findings will run counter to popular representations of the climate change topic in public discussion and the media, but they reflect our careful assessment of the best and most relevant scientific information.

2 CO₂ fertilization and global greening

The growing CO₂ concentration in the atmosphere has the important positive effect of promoting plant growth by enhancing photosynthesis and improving water use efficiency. That is evident in the “global greening” phenomenon discussed below, as well as in the improving agricultural yields discussed in Section XX.

2.1 CO₂ and global greening

“Greening” refers to an increase in the fraction of the Earth’s surface covered by plants. It can be quantified by the “Leaf Area Index” (LAI) measured by satellite. Many studies over the past decade have confirmed a global greening pattern (increase in LAI) attributable to rising CO₂ levels. Zhu *et al.* (2016) was one of the first studies to report that global greening was detectable using satellite sensors. From 1982 to 2011 they detected greening over 25-50% of the Earth versus “browning” over only 4%, and attributed 70% of the greening to rising CO₂ levels (see Figure 2.3).

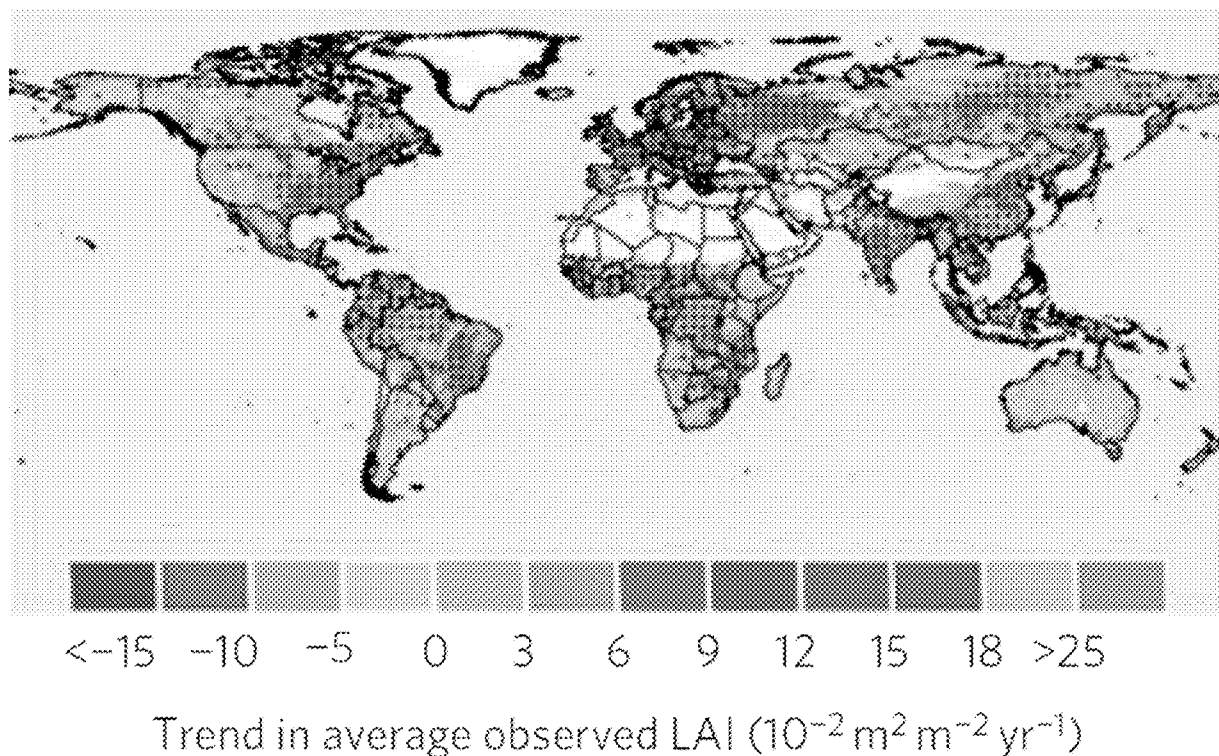


Figure 2.3: Trends in average Leaf Area Index (LAI). Source: Zhu et al. 2016 Figure 3.

Zheng (2017) confirmed the pattern, noting that greening over thirty years had added 8% to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen et al. (2019) noted that China and India were exploiting it though land management changes. Thus while China accounts for only 6.6% of global vegetated area it accounts for 25% of global net increase in LAI. Piao *et al.* (2020) noted that greening was even observable in the Arctic.

While plant models predict increases in photosynthesis should be observed in response to rising CO₂, Haverd et al. (2020) reported that observed CO₂ fertilization rate was nearly double what models

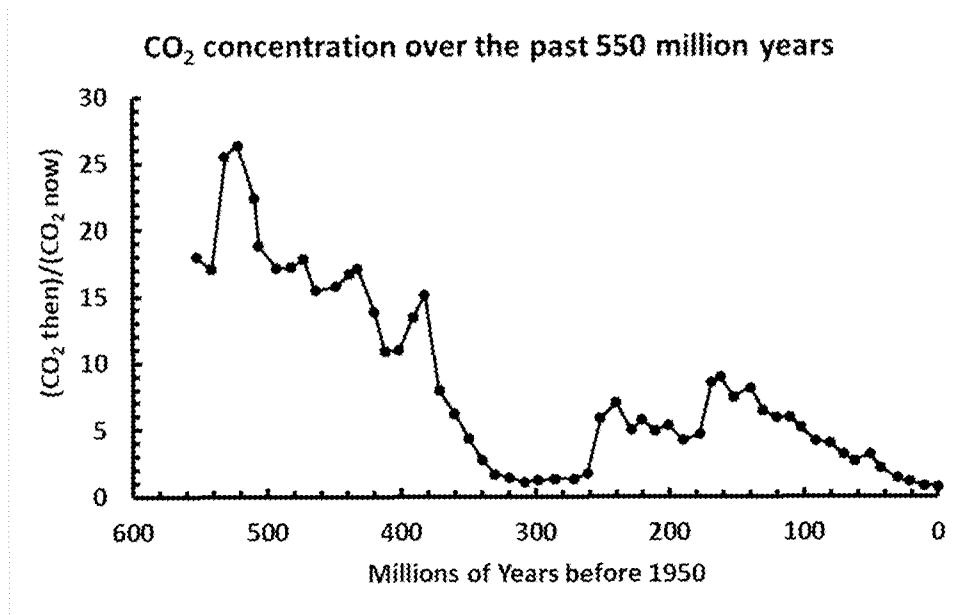
had predicted. That is, CO₂ fertilization had driven an increase in observed global photosynthesis by 30% since 1900, versus 17% predicted by plant models. Among other things this indicates that global models of the socioeconomic impacts of climate change have likely understated the benefits to crops and agriculture from rising CO₂. The connection between CO₂ fertilization and climate policy will be discussed in Chapter XX.

Finally, Chen *et al.* surveyed claims that greening had slowed since 2000 due to drought stress. They found instead that faulty satellite sensors were the cause and that the corrected data showed accelerated greening over 55% of the globe while browning was accelerating over only 7%. In other words, the greening trend continued with no evidence of slowdown, and CO₂ fertilization remained the dominant driver

2.2 Photosynthesis and CO₂ levels

Plants build biomass through *photosynthesis*, a process that converts carbon dioxide, water, and light into sugar. The plant enzyme responsible for photosynthesis is called Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO₂ is available at the surface of the RuBisCo enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass. This is referred to as the “C3” process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth’s atmospheric CO₂ levels were usually much higher than they are today, as shown in the following figure.



About 400 million years ago CO₂ levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Berner 2006, Judd et al. 2024). Over the past 35 million years the level of atmospheric CO₂ has been steadily declining. During glaciations levels have fallen as low as 170 ppm (Gerhart and Ward 2010).

In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C4, in which CO₂ is concentrated in the vicinity of Rubisco allowing for the C3 process to function more efficiently. For agricultural purposes the plant categories are:

- C3: rice, wheat, soybeans and most other crops
- C4: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth rates would have declined and eventually ceased. Below 180 ppm many C3 species experience growth rate reductions on the order of 40-60% compared to their growth rates at 350 ppm (Gerhart and Ward 2010). C3 plants have been observed under experimental conditions to stop growing altogether at levels between 60—140 ppm CO₂. Some C4 plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Currently, CO₂ levels are about 420 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 1 which is reproduced from Gerhart and Ward (2010). It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains exhibited from increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

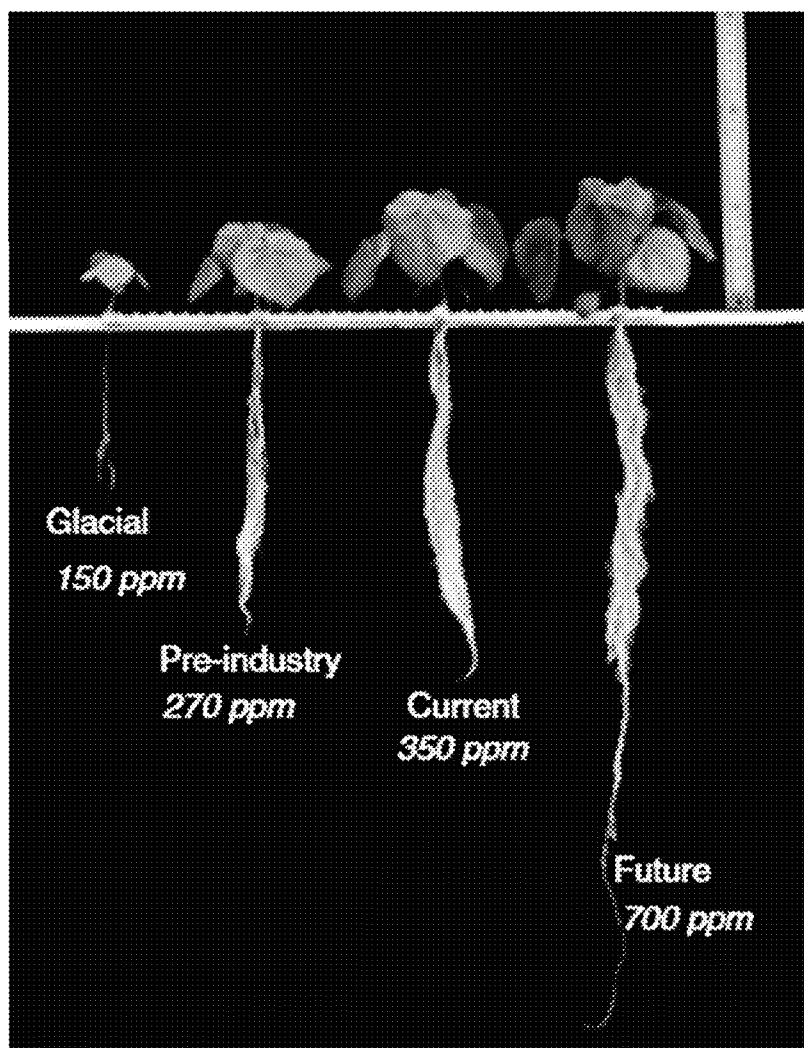


Figure 2.1: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010).

Over the past 60+ years there have been tens of thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C3 plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, which allows water to evaporate away. Under enriched CO₂ conditions the stomata are closed for longer periods helping the plant retain water longer, thereby increasing water use efficiency.

One of the ways in which scientists have studied the effects of CO₂ enrichment is through “free air enrichment experiment” or FACE plots, in which small chimneys are placed in fields surrounding plants and the growth response to elevated CO₂ under varying weather conditions are recorded. Ainsworth and Long (2021) summarize results from about 250 such studies. They conclude:

- “Across 186 independent studies of 18 C3 crops, elevation of [CO₂] by ca. 200 ppm caused a ca. 18% increase in yield under non-stress conditions.”
- “Legumes and root crops showed a greater increase and cereals less. Nitrogen deficiency reduced the average increase to 10%, as did warming by ca. 2°C.”

The authors reported that C4 plants mainly exhibited benefits during drought conditions. However additional evidence on corn growth under enhanced CO₂ levels will be provided in Section XX.

2.2 CO₂ and key global food crops - I DON'T THINK THIS SECTION IS NEEDED

Rice

Lv (2020) analyzed experimental studies done on conventional rice plants in Japan and China. They found that the type of cultivar was a determining factor in quantifying the amount of response displayed, but all cultivar types showed positive yield response to elevated CO₂ levels. An additional 200 ppm CO₂ raised rice yields by 13.5%-32.8% for three common rice cultivars. A similar meta-analysis synthesis (Hu, 2021) was done for all available FACE studies on rice. On average, elevated CO₂ enhanced rice yields by 16.2% and improved their leaf photosynthesis. Hybrid rice displayed a greater yield enhancement (24.7%) than conventional rice (14.2%). The synthesis also revealed that yield response to elevated CO₂ was constrained by changes in nitrogen availability and temperatures. Ainsworth and Long (2021) argued that if farmers are careful in choosing the rice variety with the highest yield potential, they will show as much as 35% yield increase from an extra 200 ppm CO₂ compared to 14% without adaptation.

Potatoes

Lee (2020) grew potato plants under elevated CO₂ concentration and reported they “yielded a distinct increase in growth and development and canopy net photosynthetic rate during tuber initiation and bulking. Consequently, biomass and canopy net photosynthesis increased, and tuber yield increased by 20.3%. The CO₂Science.org website reports on 33 published experiments between 1988 and 2019 exposing potatoes to enriched CO₂ levels. Converted to a common +300ppm scale the average photosynthesis rate change was +50.3 percent.

Soybean

Studies on the impact of elevated CO₂ on Soybean (*Glycine max* (L.) Merr.) plants in the water-deficient region of Huang-Huai-Hai Plain, China, showed that elevated CO₂ concentrations resulted in improved photosynthesis rate, water use efficiency and growth (Li, 2013) under both normal conditions and drought conditions. The CO₂Science.org website reports on 108 published experiments between 1985 and 2019 exposing soybean to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +50.9 percent. In addition there were 10 studies reporting on +600 ppm CO₂ enrichment, resulting in an average increase in photosynthesis of 90.3%.

Maize (corn)

The CO₂Science.org website reports on 28 published experiments between 1983 and 2018 exposing corn (*Zea mays* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +23.7 percent. Corn also benefits from increased drought tolerance under elevated CO₂. An experimental study (Allen Jr, 2011) exposed plants to water stress conditions in sunlit controlled-

environment chambers at 360 ppm (ambient) and 720 ppm (elevated) CO₂. The drought stress caused a 41% loss of growth under ambient CO₂ but only a 13% loss under elevated CO₂.

Wheat

The CO2Science.org website reports on 92 published experiments between 1983 and 2020 exposing common wheat (*Triticum aestivum* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +67.6 percent. Blandino (2020) measured the yield as well as nutritional quality of an “improver” hybrid wheat variety and its parents under elevated CO₂ levels (+166 ppm). They reported a grain yield increase of +16% but a 7% decrease in grain protein levels. But they found that the food quality of different wheat varieties responded differently to elevated CO₂ levels, so that with proper varietal selection end-users can select wheat types that best take advantage of the elevated CO₂.

Coffee

The CO2Science.org website reports on 18 published experiments between 2013 and 2020 exposing coffee (*Coffea arabica*) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +110.9 percent. To forecast the future impact of climate on coffee yields, Verhage (2017) analyzed yield data over 1989 to 2013 from 42 municipalities in Brazil. The study found that “yield losses due to high air temperatures and water deficit will increase, while losses due to frost will decrease. Nevertheless, extra losses are offset by the CO₂ fertilization effect, resulting in a net increase of the average Brazilian Arabica coffee yield of 0.8% to 1.48 t ha⁻¹ in 2040-2070”.

Specific effects of climate change on US agriculture will be reviewed in Chapter XX.

2.3 Rising CO₂ and crop water use efficiency

Deryng *et al.* (2016) surveyed evidence on crop water productivity (CWP, the yield per unit of water used), drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them so that all regions showed a net CWP gain. Deryng *et al.* (2016) also reported that negative impacts of warming on wheat and soybean yields from what?? were fully offset by CWP gains and mitigated by up to 90% for rice and 60% for maize.

I don't think the figure is needed or particularly useful?

Figure 2.2 shows their Deryng *et al.*'s results. The gray bars report yield changes under warming alone and the green bars show the effects of warming after accounting for the CO₂ fertilization effect.

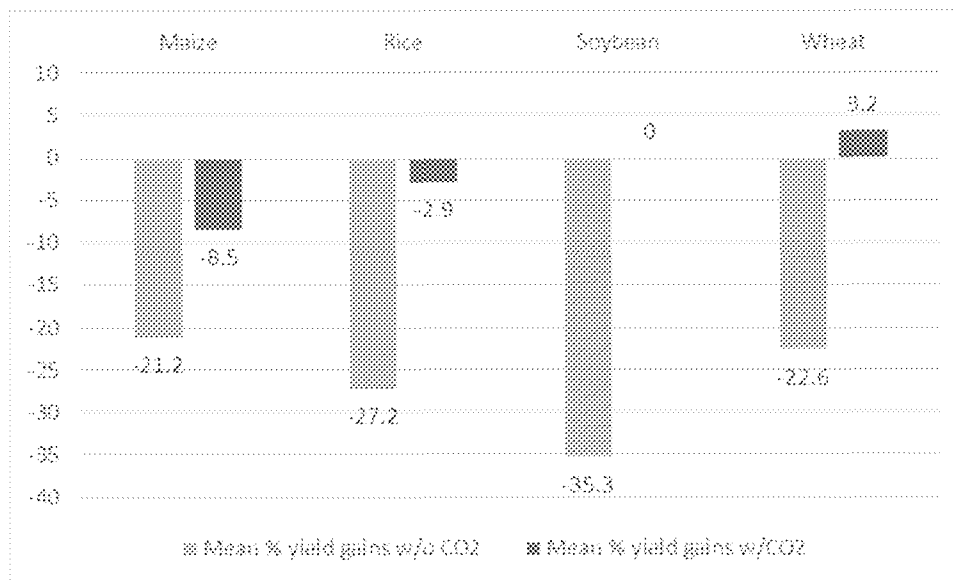


Figure 2.2: mean yield changes under RCP8.5 as of 2080 without CO₂ fertilization (gray) and with CO₂ fertilization (green). Data from Deryng et al. (2016).

Similarly, Cheng *et al.* (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that, despite the extra biomass, global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

2.5 Concealment of CO₂ fertilization benefits in IPCC Reports

If CO₂ emissions had been discovered to be causing global crop declines and regional browning, that surely would have been discussed prominently in IPCC reports, perhaps even with its own chapter in an Assessment Report if not an IPCC Special Report on its own. By contrast the IPCC has been almost silent on the topic of global greening.

~~Working Group I Summary for Policymakers: No mention.~~

~~Working Group I Technical Summary: No mention of greening. CO₂ fertilization mentioned twice: as a contributor via plant growth to the land carbon sink and as a contributor to the increased amplitude of the seasonal CO₂ cycle.~~

~~Working Group II Summary for Policymakers: No mention of greening except the observation that adding forest cover to cities can locally reduce temperatures. No mention of CO₂ fertilization.~~

~~Working Group II Technical Summary: No mention.~~

~~AR6 Synthesis Report: No mention.~~

~~AR6 Summary of Synthesis Report: (called the “Longer Report”): No mention.~~

The topic is briefly acknowledged in a few places in the body of the IPCC 6th Assessment Report but is omitted in all Summary documents. For example, Section 2.3.4.3.3 of the AR6 Working Group I report, entitled “global greening and browning,” points out that the IPCC Special Report on Climate Change and Land had concluded with high confidence that greening had increased globally over the past 2-3 decades. It then discusses the various estimate of greening trends and notes that there are variations in the estimates among data sets so that there is high confidence that greening has occurred, but low confidence in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports. ~~But as noted, despite the volume of supporting evidence, news about global greening, improved plant water use efficiency and gains in crop production is omitted from the Summaries for Policymakers.~~

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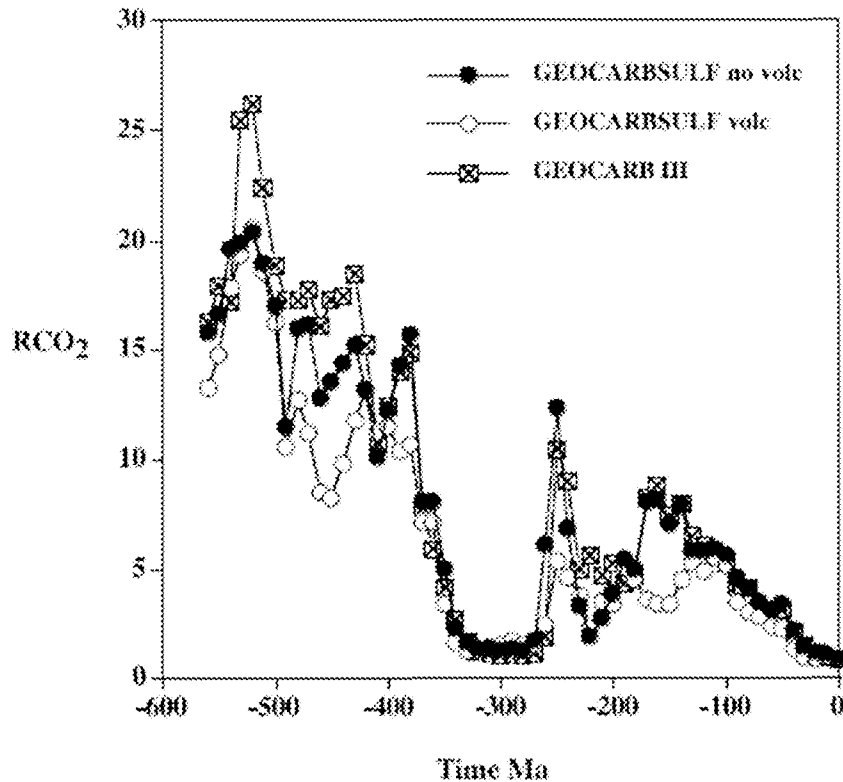
2 CO₂ and global greening

The term “**photosynthesis**” describes the process by which plants build biomass by converting light energy into chemical energy, which is then used to synthesize organic compounds (i.e. grow). Plant photosynthesis requires carbon dioxide (CO₂), water (H₂O), and light. The plant enzyme responsible for photosynthesis is called Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO₂ is available at the surface of the RuBisCo enzyme. The carbon is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass, which is referred to as the C3 process. Rubisco is estimated to have evolved about 3 billion years ago. During the past 400 million years the level of atmospheric CO₂ has been quite low in comparison to the several billion years preceding, which threatened plant survival. In response, beginning about 35 million years ago some plants evolved another photosynthetic pathway called C4, in which CO₂ is concentrated in the vicinity of Rubisco allowing for the C3 process to function more efficiently. For agricultural purposes the plant categories are:

- C3: rice, wheat, soybeans and most other crops
- C4: maize (corn), millet, sorghum

Hence the response of C3 plants to elevated CO₂ levels is of particular importance when assessing the potential benefits of rising CO₂ emissions.

Currently, CO₂ levels are about 420 ppm, up from 280 ppm in the early 1800s. On the time scale of evolution this is a relatively low level. There have been several estimates of the atmospheric CO₂ concentration over geological time scales. Berner (2006) shows past CO₂ values relative to the modern level (=1.0). Levels were many times higher (3—20x) through much of Earth’s history compared to the past million years or so.



Source: Berner, R.A. GEOCARBSULF: A combined model for Phanerozoic atmospheric O₂ and CO₂. *Geochimica et Cosmochimica Acta* 70 (2006) 5653–5664.

A more recent reconstruction from Judd et al. (2024) is very similar but exhibits smaller swings. Both reconstructions indicate that atmospheric CO₂ levels were approximately 1,000 ppm or more for much of the past 250 million years. So it should come as no surprise that plants respond positively to rising CO₂ levels.

Plant Responses to Elevated CO₂ Levels

Over the past 60+ years there have been tens of thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that, as expected, plants benefit from extra CO₂. C3 plants exhibit a more rapid growth response than C4 plants, but both types benefit. The mechanisms by which plants benefit from the extra CO₂ are:

- Enhanced photosynthesis via the metabolic pathways described above
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, which allows water to evaporate away. Under enriched CO₂ conditions the stomata are closed for longer periods helping the plant retain water longer, thereby increasing water use efficiency.

Many studies are summarized at the CO₂Science website:

http://www.co2science.org/data/plant_growth/plantgrowth.php

Some examples are provided below.

FACE Experiments

One of the ways scientists have studied the effects of CO₂ enrichment is through “free air enrichment experiment” or FACE plots, in which small chimneys are placed in fields surrounding plants and the growth response to elevated CO₂ under varying weather conditions are recorded.

Ainsworth et al. (2020) summarizes results from about 250 such studies:

- Ainsworth, Elizabeth and Stephen P. Long (2020) 30 years of free-air carbon dioxide enrichment (FACE): What have we learned about future crop productivity and its potential for adaptation? *Global Change Biology* <https://doi.org/10.1111/gcb.15375>

Highlights:

- “Across 186 independent studies of 18 C3 crops, elevation of [CO₂] by ca. 200 ppm caused a ca. 18% increase in yield under non-stress conditions.”
- “Legumes and root crops showed a greater increase and cereals less. Nitrogen deficiency reduced the average increase to 10%, as did warming by ca. 2°C.”

The authors reported that C4 plants mainly exhibited benefits during drought conditions. However additional evidence on corn growth under enhanced CO₂ levels will be provided below.

1.1 FOOD CROPS

1.1.1 Rice

Rice, a C3 plant, responds positively to elevated CO₂. To determine the dominant factor contributing to the higher yield response to elevated CO₂, Lv (2020) analyzed experimental studies done on conventional rice plants in Japan and China. It was found out that the type of cultivar was a determining factor in quantifying the amount of response displayed, but all cultivar types showed positive yield response to elevated CO₂ levels.

“Elevated [CO₂] (~200 μmol mol⁻¹ above ambient) increased rice yields by 13.5% (n = 93), 22.6% (n = 10) and 32.8% (n = 17) for japonica, indica and hybrid cultivars.”

A similar meta-analysis synthesis (Hu, 2021) was done for all available experimental studies on Free Air CO₂ Enrichment (FACE) response of rice. On average, elevated CO₂ enhanced rice yields by 16.2% and improved their leaf photosynthesis. Hybrid rice displayed a greater yield enhancement (24.7%) than conventional rice (14.2%). The synthesis also revealed that yield response to elevated CO₂ was constrained by changes in nitrogen availability and temperatures.

Further, if farmers are careful in choosing the rice variety with the highest yield potential, it is estimated that they will show as much as 35% yield increase (Ainsworth and Long 2021) in elevated CO₂ compared to an average of around 14%.

Citations:

- Lv, C. H. (2020). Response of rice yield and yield components to elevated [CO₂]: a synthesis of updated data from FACE experiments. *European Journal of Agronomy*, 112, 125961.
- Hu, S. W. (2021). Response of rice yield traits to elevated atmospheric CO₂ concentration and its interaction with cultivar, nitrogen application rate and temperature: a meta-analysis of 20 years FACE studies. *Science of the Total Environment*, 764, 142797.
- Ainsworth, E. and S. Long (2021). 30 years of free-air carbon dioxide enrichment (FACE): What have we learned about future crop productivity and its potential for adaptation? *Global Change Biology*, 27(1), 27-49.

1.1.2 Potatoes

In experiments in South Korea, potato plants under elevated CO₂ concentration “yielded a distinct increase in growth and development and canopy net photosynthetic rate during tuber initiation and bulking. Consequently, biomass and canopy net photosynthesis increased, and tuber yield increased by 20.3%

- Lee, Y. S. (2020). The effect of concurrent elevation in CO₂ and temperature on the growth, photosynthesis, and yield of potato crops. *PLoS One*, 15(10), e0241081.

The CO₂Science website reports on 33 published experiments between 1988 and 2019 exposing potatoes to enriched CO₂ levels. Converted to a common +300ppm scale the average photosynthesis rate change was +50.3 percent.

http://www.co2science.org/data/plant_growth/photo/s/solanumt.php

1.1.3 Soybean

Studies on the impact of elevated CO₂ on Soybean (*Glycine max* (L.) Merr.) plants in the water-deficient region of Huang-Huai-Hai Plain, China, showed that elevated CO₂ concentrations resulted in improved photosynthesis rate, water use efficiency and growth (Li, 2013) under both normal conditions and drought conditions.

- Li, D. L. (2013). Effects of elevated CO₂ on the growth, seed yield, and water use efficiency of soybean (*Glycine max* (L.) Merr.) under drought stress. *Agricultural Water Management*, 129, 105-112.

The CO₂Science website reports on 108 published experiments between 1985 and 2019 exposing soybean to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +50.9 percent. In addition there were 10 studies reporting on +600 ppm CO₂ enrichment, resulting in an average increase in photosynthesis of 90.3%.

http://www.co2science.org/data/plant_growth/photo/g/glycinem.php

1.1.4 Maize

An experimental study (Allen Jr, 2011) of maize in “sunlit controlled-environment chambers at 360 (ambient) and 720 (double-ambient, elevated) $\mu\text{mol mol}^{-1}$ carbon dioxide concentrations [CO₂]” were exposed to water stress conditions. It was found that “cumulative photosynthesis of drought-stress maize, compared to well-watered plants, was 41% lower under ambient [CO₂] but only 13% lower under elevated [CO₂].” In drought conditions, young maize plants used water more efficiently at elevated [CO₂] than at ambient [CO₂]. The researcher summarizes that

“drought stress in C₄ crop plants can be ameliorated at elevated [CO₂] as a result of lower stomatal conductance and sustaining intercellular [CO₂]. Furthermore, less water might be required for C₄ crops in future higher CO₂ atmospheres, assuming weather and climate similar to present conditions (Allen Jr, 2011).”

- Allen Jr, L. K. (2011). Elevated CO₂ increases water use efficiency by sustaining photosynthesis of water-limited maize and sorghum. *Journal of Plant physiology*, 168(16), 1909-1918.

The CO₂Science website reports on 28 published experiments between 1983 and 2018 exposing corn (*Zea mays* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +23.7 percent.

http://www.co2science.org/data/plant_growth/photo/z/zeam.php

1.1.5 Wheat

Blandino (2020) measured the yield as well as nutritional quality of an “improver” hybrid wheat variety and its parents under elevated CO₂ levels (+166 ppm). They reported a grain yield increase of +16% but a 7% decrease in grain protein levels. They found that the food quality of different wheat varieties responded differently to elevated CO₂ levels, so that with proper varietal selection end-users can select wheat types that best take advantage of the elevated CO₂.

According to (Abdelhakim, 2021), “all genotypes of wheat showed higher photosynthetic rate and maintained maximum quantum efficiency of PSII* ” under heat stress under elevated CO₂ levels than at ambient CO₂ levels.

*Where Photosystem II (PSII) is an assembly of up to 25 proteins that carries out the conversion of solar energy and production of molecular oxygen inside plants.

- Abdelhakim, L. O. (2021). The effect of individual and combined drought and heat stress under elevated CO₂ on physiological responses in spring wheat genotypes. *Plant Physiology and Biochemistry*, 162, 301-314.
- Blandino, M. B. (2020). Elevated CO₂ impact on common wheat (*Triticum aestivum* L.) yield, wholemeal quality, and sanitary risk. *Journal of agricultural and food chemistry*, 68(39), 10574-10585.

The CO2Science website reports on 92 published experiments between 1983 and 2020 exposing common wheat (*Triticum aestivum* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +67.6 percent.

http://www.co2science.org/data/plant_growth/photo/t/triticuma.php

1.1.6 Coffee

Among beverage commodities, Arabica coffee plants are “highly suited for a changing climate” as they thrive in elevated CO₂ levels, given that light is nonlimiting (de Souza, 2023). Studies show exposure to elevated CO₂ levels, among two different type of coffee cultivars in a free-air CO₂ enrichment (FACE) facility in Latin America, resulted in high photosynthetic rates, high water-use efficiency, increased growth and higher yield (Ghini, 2015). Besides, elevated CO₂ also reduces “incidence of leaf miners (*Leucoptera coffeella*) during periods of high infestation (Ghini, 2015).”

To forecast future impact of climate on coffee yields, yield data from 1989 to 2013 in 42 municipalities in Brazil was analyzed using a model. The study (Verhage, 2017) found that climate change will overall benefit yields in Brazilian Arabica coffee regions.

“yield losses due to high air temperatures and water deficit will increase, while losses due to frost will decrease. Nevertheless, extra losses are offset by the CO₂ fertilization effect, resulting in a net increase of the average Brazilian Arabica coffee yield of 0.8% to 1.48 t ha⁻¹ in 2040-2070 (Verhage, 2017).”

- de Souza, A. d. (2023). Growth and leaf gas exchange upregulation by elevated [CO₂] is light dependent in coffee plants. *Plants*, 12(7), 1479.
- Ghini, R. T.-N.-F. (2015). Coffee growth, pest and yield responses to free-air CO₂ enrichment. *Climate Change*, 132, 307-320.
- Verhage, F. Y. (2017, November). *Carbon dioxide fertilization offsets negative impacts of climate change on Arabica coffee yield in Brazil*. Retrieved October 2024, from esalq: http://www.esalq.usp.br/departamentos/leb/eventos/Thesis_Report_-_Fabian_Verhage.pdf

The CO2Science website reports on 18 published experiments between 2013 and 2020 exposing coffee (*Coffea arabica*) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +110.9 percent.

http://www.co2science.org/data/plant_growth/photo/c/coffeaar.php

1.2 SUMMARY STATEMENTS

The foregoing points are not controversial in the scientific literature, although as I will show they are deliberately concealed from policy makers in the IPCC process. As a representation of the academic consensus consider the following selections (emphasis added) from a 2016 *Nature Climate Change* survey paper on crop water productivity (CWP), i.e. yield per unit of water used:

- Deryng, Delphine and 15 coauthors (2016) Regional disparities in the beneficial effects of rising CO₂ concentrations on crop water productivity. *Nature Clim Chg* 18 April 2016 DOI: 10.1038/NCLIMATE2995.

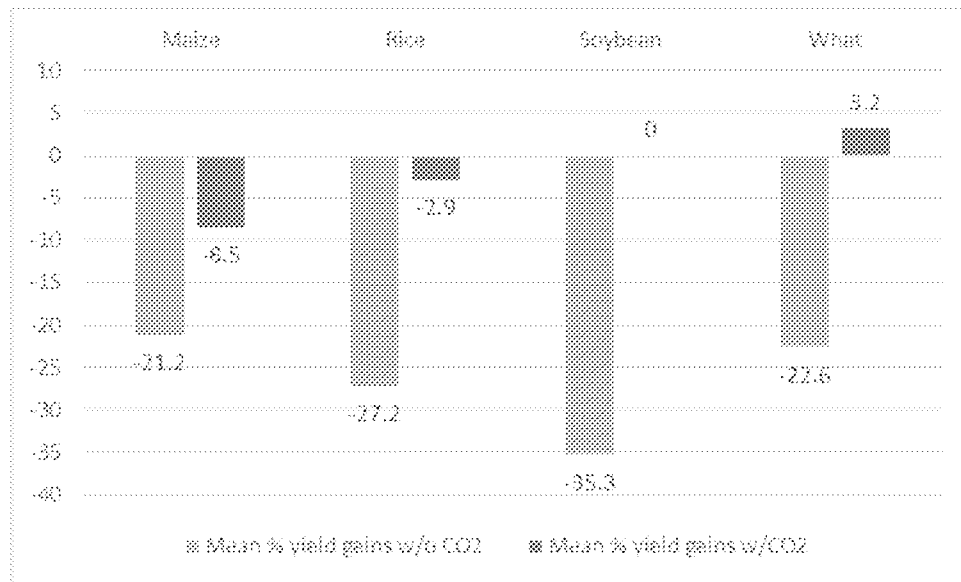
Research indicates unabated climate change will exacerbate water scarcity around the world. This is thought to threaten agricultural productivity and food security, especially in arid regions, where agriculture relies heavily on irrigation and consumes the majority of diverted freshwater. Yet, **rising atmospheric CO₂ concentrations ([CO₂]), despite directly contributing to climate change, have the potential to increase crop water productivity (CWP; defined here as the ratio of crop yield to total crop water use over the growing season) by enhancing photosynthesis and reducing leaf-level transpiration of plants.** If these effects can be harnessed to increase crop yields and reduce water consumption in agriculture at national to continental scales, this could greatly help in ensuring food and water security for a rapidly growing global population.

The enhancement of photosynthesis rates in C3 crops and the reduction in stomatal conductance and thus water loss in both C3 and C4 crops under elevated [CO₂] is well supported by numerous plant manipulation experiments. The extent to which such mechanisms eventually enhance crop yields and reduce evapotranspiration (ET) is less well understood on large scales, but observations of crops grown under elevated [CO₂] (Free Air Carbon Enrichment, FACE) show that an average increase of 13% in yields and 5% reduction in ET can be expected.

The authors went on to survey all available FACE data on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. They contrasted results from climate change alone ("CC w/o CO₂") versus climate change inclusive of CO₂ fertilization effects ("CC w/ CO₂"):

By 2080 under CC w/o CO₂, we find severe negative impacts on crop yields at the global scale and small reductions in corresponding [water usage], which together lead to large reductions in global CWP (median 13-26%, with larger reductions for C3 crops) supported by more than 80% of the simulations.... **In contrast, under CC w/CO₂, median negative impacts on yields are fully compensated for wheat and soybean, and mitigated by up to 90% for rice and 60% for maize.**

Specifically their tabulated results are:



The beneficial effect of CO₂ on CWP is remarkable (figure annotated):

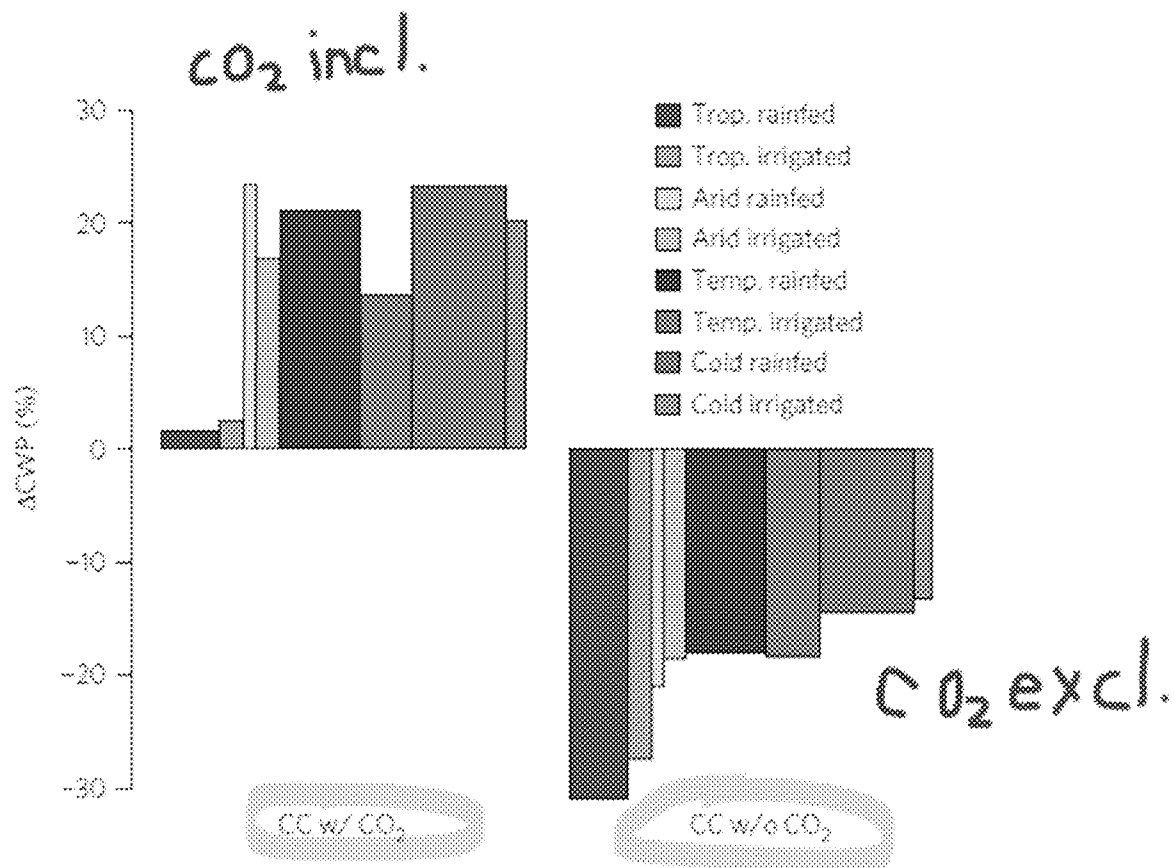


Figure 2 | Simulated CWP responses across agro-climatic regions.

The median change in rainfed and irrigated CWP (%) in tropical (trop.), arid, temperate (temp.) and cold regions simulated under RCP 8.5 by 2080 relative to 2000 for all crops—GGCMs-GCMs combinations for CC w/ CO₂ and CC w/o CO₂ only. The width of the boxes varies according to corresponding total crop irrigated and rainfed harvested areas.

The boxes on the right show climate change (mainly warming) causes CWP to fall in all regions. But once the CO₂ fertilization effect is accounted for (left side) the productivity effects all reverse and become positive.

The authors conclude:

Our results—based on state-of-the-art modelling and observational capacities—demonstrate that a robust understanding of the role of rising [CO₂] is vital to assess potentially beneficial effects on crop production and agricultural water requirements; effects which might offer crucial opportunities for food and water security in arid and semi-arid areas.... Food security, especially in arid and less developed regions, is not only a function of crop productivity and available land, but also of CWP and available water resources. This relationship is strongly affected by elevated [CO₂], and demands greater attention in scientific and policy assessment.

2 RISING CO₂ HAS GREATLY ENHANCED US AGRICULTURAL PRODUCTIVITY SINCE 1940

The following study:

- Taylor, Charles and Wolfram Schlenker (2021) Environmental drivers of agricultural productivity growth: CO₂ fertilization of US field crops. *National Bureau of Economic Research Working Paper 29320* <http://www.nber.org/papers/w29320>

presents a novel investigation of the effect of rising CO₂ on yields of corn, soybeans and rice across the US. The authors begin by noting that lab experiments report positive CO₂ effects on plant growth but may not capture real world growing conditions. FACE studies get closer to real world effects but the CO₂ enrichment is dissipated by local weather and the studies tend to be very short term. Taylor and Schlenker made use of newly-available satellite data from the Orbiting Carbon Observatory-2 (OCO-2) and from NOAA's Carbon Tracker system that estimates local CO₂ concentrations based on observations from 460 sites around the world. These provide estimates of ground-level CO₂ concentrations by location around the US. While the CO₂ level mixes globally to form an average which is the main input into climate models, at local levels it varies on short time scales based on local emissions and weather conditions.

The authors exploited this variability to investigate if rising CO₂ levels helps explain some of the impressive US agricultural productivity gains in the post-war period. They regressed county-level annual yields of corn, soybean and wheat on explanatory variables consisting of the local ambient CO₂ level, a trend term, weather variables (temperature and precipitation) and local pollution levels. Across different data sets and several different regression model specifications they found that a 10 ppm increase in CO₂ yielded a 5% increase in corn yield, 6% increase in soybean yield and 8% increase in wheat yield. These are much higher than most previous estimates. For instance the FACE studies mentioned surveyed by Ainsworth and Long as mentioned above concluded additional CO₂ only raises yields by 1—2% per additional 10 ppm CO₂. Taylor and Schlenker argue that their estimates are more accurate than FACE results because they are able to control for many real-world local outdoor conditions over relatively long time intervals.

Considering the change in atmospheric CO₂ levels since 1940 the authors estimate that CO₂ fertilization accounted for yield gains of 50%, 60% and 80% respectively of corn, soybeans and wheat, and add 1-2% annually to output of these crop types. **It would be possible to use these empirical results and historical crop and agricultural price data to estimate the dollar value of additional food production since 1940 attributable to rising CO₂ levels.**

3 GLOBAL GREENING “INDISPUTABLE”

“Greening” refers to an increase in the total amount of the Earth’s surface covered in plants. The main measure of greening is “Leaf Area Index” or LAI as measured by satellite. Many studies over the past decade have confirmed a global greening pattern (rising LAI) attributable to rising CO₂ levels.

- Zhu, Zaichun et al. (2016) Greening of the Earth and its drivers. *Nature Climate Change* 6 Aug 2016 <https://www.nature.com/articles/nclimate3004>
 - Greening has been detected by satellites over 25-50% of the Earth versus browning over only 4%; 70% of the greening is attributable to rising CO₂ levels

“Here we use three long-term satellite leaf area index (LAI) records and ten global ecosystem models to investigate four key drivers of LAI trends during 1982–2009. We show a persistent and widespread increase of growing season integrated LAI (greening) over 25% to 50% of the global vegetated area, whereas less than 4% of the globe shows decreasing LAI (browning). Factorial simulations with multiple global ecosystem models suggest that CO₂ fertilization effects explain 70% of the observed greening trend, followed by nitrogen deposition (9%), climate change (8%) and land cover change (LCC) (4%). CO₂ fertilization effects explain most of the greening trends in the tropics, whereas climate change resulted in greening of the high latitudes and the Tibetan Plateau.”
- Zeng, Zhenzhong et al. (2017) Climate mitigation from vegetation biophysical feedbacks during the past three decades. *Nature Climate Change* 7:432-436 May 2017 <https://www.nature.com/articles/nclimate3299>
 - Global greening is unequivocal and in addition to increased plant growth it has slowed warming by 12% over the previous 30 years.

“Satellite data show unequivocally that the land surface has been greening for the past 30 years, and that leaf area index (LAI) has increased by 8% globally. This satellite-observed greening of the Earth is supported by increased biomass from long-term forest inventories, model simulations and observed enhancement of seasonal exchange of CO₂. The increased photosynthetic removal of CO₂ from the atmosphere and consequent carbon sequestration potentially driven by this greening impose a negative forcing on the climate system... We found that the observed greening partly mitigated the warming induced by rising greenhouse gases, primarily through increased evapotranspiration. We emphasize the importance of model calibration to realistically simulate transpiration processes and biophysical feedbacks. This work highlights the importance of the biophysical feedbacks in the climate system, and the potential of greening to mitigate climate change.”
- Chen, Chi et al. (2019) China and India lead in greening of the world through land-use management. *Nature sustainability* 2:122-129 <https://www.nature.com/articles/s41893-019-0220-7>
 - China and India are taking advantage of rising CO₂ through land use changes to achieve large growth gains in forests and croplands.

“Satellite data show increasing leaf area of vegetation due to direct factors (human land-use management) and indirect factors (such as climate change, CO₂ fertilization, nitrogen deposition and recovery from natural disturbances). Among these, climate change and CO₂ fertilization effects seem to be the dominant drivers. However, recent satellite data (2000–2017) reveal a greening pattern that is strikingly prominent in China and India and

overlaps with croplands world-wide. China alone accounts for 25% of the global net increase in leaf area with only 6.6% of global vegetated area. The greening in China is from forests (42%) and croplands (32%), but in India is mostly from croplands (82%) with minor contribution from forests (4.4%). China is engineering ambitious programmes to conserve and expand forests with the goal of mitigating land degradation, air pollution and climate change. Food production in China and India has increased by over 35% since 2000 mostly owing to an increase in harvested area through multiple cropping facilitated by fertilizer use and surface- and/or groundwater irrigation. Our results indicate that the direct factor is a key driver of the 'Greening Earth', accounting for over a third, and probably more, of the observed net increase in green leaf area."

- Piao Shilong et al. (2020) Characteristics, drivers and feedbacks of global greening *Nature Reviews Earth & Environment* 1:14-27

- Satellite data back to 1981 reveals global greening which is especially strong in heavily farmed or afforested areas including China and India; CO₂ is the main driver; greening mitigates global warming.

"Vegetation greenness has been increasing globally since at least 1981, when satellite technology enabled large-scale vegetation monitoring. ... Greening is pronounced over intensively farmed or afforested areas, such as in China and India, reflecting human activities. However, strong greening also occurs in biomes with low human footprint, such as the Arctic, where global change drivers play a dominant role. Vegetation models suggest that CO₂ fertilization is the main driver of greening on the global scale, with other factors being notable at the regional scale. Modelling indicates that greening could mitigate global warming by increasing the carbon sink on land and altering biogeophysical processes, mainly evaporative cooling."

- Haverd, Vanessa et al. (2020) Higher than expected CO₂ fertilization inferred from leaf to global observations. *Global Change Biology* 26: 2390–2402.

<https://onlinelibrary.wiley.com/doi/epdf/10.1111/gcb.14950>

- Plant-level models predict CO₂ uptake changes at only about half the rate consistent with evidence of global greening: Haverd et al. show that the plant models fail to include key photosynthesis response mechanisms and actual land carbon sink will be much higher than current models show.

"Global terrestrial gross primary production (GPP)—the rate of carbon fixation by photosynthesis—is estimated to have risen by (31 ± 5)% since 1900, but the relative contributions of different putative drivers to this increase are not well known. Here we identify the rising atmospheric CO₂ concentration as the dominant driver. We reconcile leaf-level and global atmospheric constraints on trends in modeled biospheric activity to reveal a global CO₂ fertilization effect on photosynthesis of 30% since 1900, or 47% for a doubling of [atmospheric CO₂] above the pre-industrial level. Our historic value is nearly twice as high as current estimates (17 ± 4)% that do not use the full range of available constraints. Consequently, under a future low-emission scenario, we project a land carbon sink (174 PgC, 2006–2099) that is 57 PgC larger than if a lower CO₂ fertilization effect comparable with current estimates is assumed."

- Zhang et al. (2024) Less than 4% of dryland areas are projected to desertify despite increased aridity under climate change. *Nature Communications Earth and Environment* 5 June 2024 <https://www.nature.com/articles/s43247-024-01463-y>

- Models predict drylands will expand under climate warming but data show the opposite: greening is happening in arid areas; the models are wrong; CO₂ fertilization accounts for the difference and by 2050 less than 4% of dryland areas will desertify under climate change

“Future projections show continued increases in aridity due to climate change, suggesting that drylands will expand. In contrast, satellite observations indicate an increase in vegetation productivity. Given the past inconsistency between the Aridity Index changes and observed vegetation changes, the future evolution of vegetation productivity within the drylands remains an open question. Here we used a data driven approach to show that increasing aridity in drylands won’t lead to a general loss of vegetation productivity. Most of the global drylands are projected to see an increase in vegetation productivity due to climate change through 2050. The aridity index will not be a good indicator of drylands in future climates. We found a broad boost to dryland vegetation productivity due to the carbon dioxide (CO₂) fertilization effect that is negated by climate changes in at most 4% of global drylands to produce desertification.”

- Chen, Xin (2024) The global greening continues despite increased drought stress since 2000. *Global Ecology and Conservation* 49 e02791

<https://www.sciencedirect.com/science/article/pii/S2351989423004262>

- Global greening is indisputable; some recent studies suggested it slowed down after 2000 but this was due to faulty satellite sensors; corrected data shows the rate of greening has accelerated; drought in some areas slowed but did not stop it.

“The global greening is an indisputable fact... The CO₂ fertilization along with land management determined that greening is dominant. However, recently global browning signals due to drought stress have also been widely reported. In this study, we used the four latest leaf area index (LAI) datasets to explore this controversial topic, and found that global greening was not only present (trend between $3.1\text{--}6.4 \times 10^{-3} \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1}$) but also continued (growth rate trend between $3.3\text{--}6.4 \times 10^{-4} \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-2}$) during 2001–2020. Greening acceleration occurred in 55.15% of the globe (positive trend and positive growth rate trend), while browning acceleration occurred in only 7.28% (negative trend and positive growth rate trend). Combined with meteorological variables, we found that CO₂ change dominated the LAI trend, while climate change largely determined the LAI growth rate trend. Importantly, our study highlighted that drought trend did not necessarily trigger vegetation browning, but slowed down the rate of greening.”

4 CONCEALMENT OF CO₂ FERTILIZATION BENEFITS IN IPCC AR6 REPORT

The enormous accumulation of evidence of CO₂ fertilization and global greening is briefly acknowledged in a few places in the body of the IPCC 6th Assessment Report but is completely omitted in all Summary documents. To prove that the IPCC is aware of the literature I first review what is said in the body of the report, then show the treatment in the IPCC Summaries.

4.1 WORKING GROUP I REPORT BODY: LIMITED ACKNOWLEDGEMENT

The body of the report takes a grudging view of the matter and over-emphasizes minor differences in estimated trends in order to justify claims of low confidence in the phenomenon.

Chapter 2 (Changing State of the Climate System) Section 2.3.4.3.3 Global greening and browning

“The AR5 WGII briefly discussed changes in global vegetation greenness derived from satellite proxies for photosynthetic activity. Observed trends varied in their strength and consistency, and AR5 thus made no confidence statement on observed changes. The [Special Report on Climate Change and Land SRCCL] subsequently concluded that greening had increased globally over the past 2–3 decades (*high confidence*).”

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“Vegetation index data derived from AVHRR and MODIS depicts increases in aspects of vegetation greenness (i.e., green leaf area and/or mass) over the past four decades (Piao et al., 2020). NDVI increased globally from the early 1980s through the early 2010s Y. Liu et al., 2015a). N. Pan et al. (2018) found NDVI increases over about 70% of the Earth’s vegetated surface through 2013, and Osborne et al. (2018) noted strong upward changes in NDVI in the circumpolar Arctic through 2016. Globally integrated Leaf Area Index (LAI) also rose from the early 1980s through at least the early 2010s (Zhu et al., 2016; Forzieri et al., 2017; Jiang et al., 2017; Xiao et al., 2017) and probably through near-present; for example, C. Chen et al. (2019) documented an LAI increase over one-third of the global vegetated area from 2000–2017. ...” [Discussion of regional results].

“Global-scale linear trends differ substantially across products for the same periods and trend metrics used (Jiang et al., 2017). Several factors contribute to this large span in estimated changes. Remotely sensed vegetation products vary in their spatial and temporal completeness as well as resolution and are sensitive to contamination from atmospheric composition, clouds, snow cover, and anisotropy, as well as orbital changes and sensor degradations (de Jong et al., 2012; Zhu et al., 2016; Jiang et al., 2017; Xiao et al., 2017; N. Pan et al., 2018). Ground-based measurements suitable for calibration and validation are scarce before 2000 (Xiao et al., 2017), and the recalibration of satellite records (e.g., as in from MODIS Collection 5 to 6) can affect trends (Piao et al., 2020). It is possible that the increase in greenness over 2000–2015 is larger than the increase in gross primary production (based on flux tower measurements and MODIS Collection 6 data) (L. Zhang et al., 2018). Land use

changes and altered disturbance regimes (e.g., floods, fires, diseases) may mask large-scale signals (Franklin et al., 2016). In addition, there is a plethora of models for the identification of phenological metrics from satellite data as well as a variety of statistical techniques for analysing historical changes (S. Wang et al., 2016)."

"In summary, there is *high confidence* that vegetation greenness (i.e., green leaf area and/or mass) has increased globally since the early 1980s. However, there is *low confidence* in the magnitude of this increase owing to the large range in available estimates."

p. 202 Chapter Summary: "Since the early 1980s, there has been a global-scale increase in the greenness of the terrestrial surface (*high confidence*)."

Chapter 3 (Human Influence on the Climate System)

p. 487: [discussion of increased amplitude of annual CO₂ cycle due to enhanced CO₂ fertilization; acknowledges evidence of CO₂ fertilization but finds a study that argues land use changes contributed more to greening than previously acknowledged.]

"...Based on available literature, CO₂ fertilization has been the main driver of the observed greening trend, but there is only *low confidence* in this assessment because of ongoing debate about the relative roles of CO₂ fertilization, high latitude warming, and land management, and the low number of models that represent the whole suite of processes involved."

p. 427 Chapter Summary (emphasis in original): **The main driver of the observed increase in the amplitude of the seasonal cycle of atmospheric CO₂ is enhanced fertilization of plant growth by the increasing concentration of atmospheric CO₂ (*medium confidence*).** However, there is only *low confidence* that this CO₂ fertilization has also been the main driver of observed greening because land management is the dominating factor in some regions.

Chapter 8 (Water Cycle Changes)

p. 1084: (Commenting on trend towards increased transpiration and evaporation):

"Using satellite and ecosystem models, Zhu et al. (2016) found a positive trend in leaf area index during 1982–2009, indicating that greening could contribute to the observed positive trend of evapotranspiration, in line with similar studies that focused on the 1981–2012 (Y. Zhang et al., 2016) and 1982–2013 (K. Zhang et al., 2015) periods. Zeng et al. (2018) determined that the 8% global increase in satellite observed leaf area index between the 1980s and the 2010s may explain an increase in evapotranspiration of 12.0+/- 2.4 mm yr⁻¹ (about 55 +/- 25% of the total observed increase). Forzieri et al. (2020) estimated that the recent increase in leaf area index led to 3.66+/-0.45 W m⁻² in latent heat flux (about 51 +/-6 mm yr⁻¹) and that the sensitivity of energy fluxes to leaf area index increased by about 20% over the 1982–2016 period. Overall, there is *medium confidence* that greening has contributed to the global increase in evapotranspiration since the 1980s.

Plant water use efficiency (WUE) is expected to rise with CO₂ levels (high confidence) (Section 8.2.3.3 and Box 5.2), and can in theory counteract rising evapotranspiration in a warmer atmosphere (Section 8.2.3.3). However, observational studies suggest that this may not be the case in some ecosystems...

...In summary, there is *high confidence* that terrestrial evapotranspiration has increased since the 1980s. There is *medium confidence* that this trend is driven by both increasing atmospheric water demand and vegetation greening, and *high confidence* that it can be partly attributed to anthropogenic forcing. There is *low confidence* about the extent to which

increases in plant water use efficiency have influenced observed changes in evapotranspiration.

4.2 WORKING GROUP II REPORT BODY: BRIEF MENTION

Chapter 2 (Terrestrial and Freshwater Ecosystems and Their Services)

p. 238: “Widespread vegetation greening, as projected in AR4, is occurring in arid shrublands (Zhang et al., 2019a; Maestre et al., 2021) as a result of increases in leaf area, woody cover and herbaceous production at desert–grassland interfaces (Gonsamo et al., 2021). Plant productivity in arid regions has increased (Fensholt et al., 2012) because of improved water-use efficiency associated with elevated CO₂ (Norby and Zak, 2011; Donohue et al., 2013; Burrell et al., 2020; Gonsamo et al., 2021) (*medium evidence, high agreement*)...”

Chapter 4 (Water)

Executive Summary (p. 564) “Rising atmospheric CO₂ generally decreases plant transpiration, affecting soil moisture, runoff, stream flows, the return of moisture to the atmosphere and surface temperature (Skinner et al., 2017). However, in some regions, these can be offset by increased leaf area (‘global greening’) driven by elevated CO₂, land use change, nitrogen deposition and effects of climate change itself (Zhu Z. et al., 2016; Zeng Z. et al., 2018).”

4.3 WORKING GROUPS I & II SUMMARY DOCUMENTS: NO MENTION

WGI Summary for Policymakers: No mention.

WGI Technical Summary: No mention of greening. CO₂ fertilization mentioned twice: as a contributor via plant growth to the land carbon sink and as a contributor to the increased amplitude of the seasonal CO₂ cycle.

WG2 Summary for Policymakers: No mention of greening except that adding forest cover to cities can locally reduce temperatures. No mention of CO₂ fertilization.

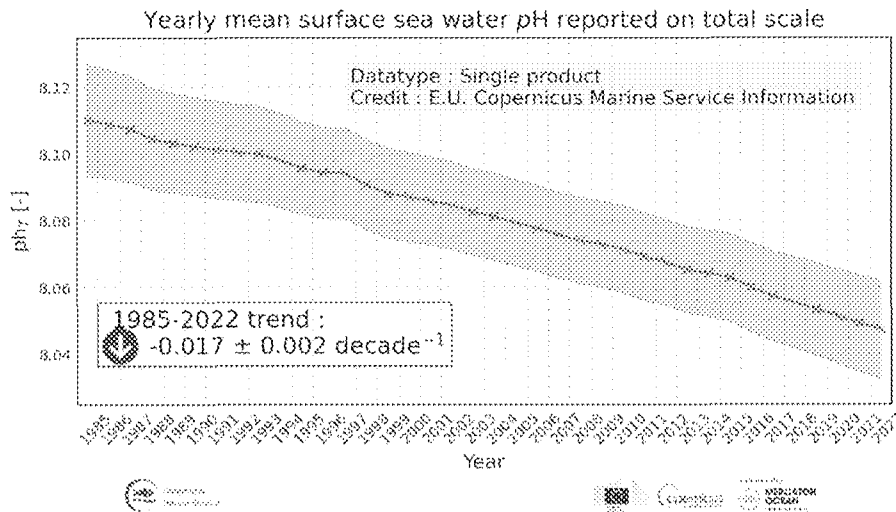
WG2 Technical Summary: No mention.

Synthesis Report: No mention.

Summary of Synthesis Report: (called the “Longer Report”): No mention.

3. Increasing CO₂ and the Alkaline Oceans

The modern-day global average pH of sea water is estimated to be 8.1, down from an estimated value of 8.2 in pre-Industrial times (Gattuso and Hansson, 2011).¹ As CO₂ concentrations in the atmosphere increase, more is absorbed by the oceans. Depending upon the alkalinity (buffering capacity) of the oceans, the oceans are expected to become somewhat less alkaline over time, putatively explaining the decrease in pH from 8.2 to 8.1 over the last few hundred years.



While this process is often called “ocean acidification”, it is a misnomer because the oceans are not expected to become acidic; “ocean neutralization” would be more accurate. And even if the water were to turn acidic, it is believed that life in the oceans evolved when the oceans were mildly acidic with pH 6.5 - to 7.0 (Krissansen-Totton et al., 2018).

It had long been assumed that a decreasing pH of sea water would reduce the calcification rate of coral reefs. But coral reefs already endure large swings in pH, partly due to daily photosynthetic activity in the reef; measured pH values range from 9.4 during the day to 7.5 at night (Revelle and Fairbridge, 1957).

In 2009 it was reported that a portion of Australia’s Great Barrier Reef (GBR, the world’s largest coral reef ecosystem) had experienced a 14% decline in calcification since 1990 (De’ath et al., 2009). This was tentatively attributed to increasing water temperature and decreasing pH. But that report was shown to have resulted from a biased data analysis (Ridd et al., 2013) which, when corrected, showed no change in calcification rates. Nevertheless, the alarm produced by the original paper has persisted as evidenced by the large number of published citations (541) received by the original study as compared to only 11 citations for the subsequent study (as of 30 April 2025).

Given the reported declines in GBR calcification between 1990 and 2009, it has come as a surprise that the decline reversed over the last decade or so, with Woods Hole Oceanographic Institution asking, “*Is the Great Barrier Reef Making a Comeback?*” (Woods Hole, 2023). The most recent annual summary of GBR conditions from the Australian Institute of Marine Science was titled, *Continued Coral Recovery*

¹ A neutral aqueous solution has a pH of 7.0, while one with pH > 7.0 is basic and pH < 7 is acidic.

Leads to 36-year Highs across Two-Thirds of the Great Barrier Reef (AIMS, 2022). Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden et al., 2015), and recovery of the reef from storm damage takes years.

On the time scale of thousands of years, boron isotope proxy measurements of pH show that ocean pH was around 7.4 or 7.5 during the last glaciation (up to about 20,000 years ago) increasing to present-day values as the world warmed during deglaciation (Rae et al., 2018). Thus, there appears to be considerable resilience of ocean biota to natural long-term changes in ocean pH since marine organisms are exposed to wide ranges in pH anyway.

It is being increasingly recognized that publication bias (alarming ocean acidification results preferred by high-impact research publications) exaggerates the impacts of declining ocean pH. An ICES Journal of Marine Science Special Issue addressed this problem with an article entitled, *Towards a Broader Perspective on Ocean Acidification Research*. In the Introduction to that Special Issue, H. I. Browman stated, "As is true across all of science, studies that report no effect of ocean acidification are typically more difficult to publish." (Browman, 2016)

Similarly, a meta-analysis of the negative effects of ocean acidification on reef fishes found that initially dramatic conclusions published in the scientific literature were all but refuted upon subsequent analysis involving larger sample sizes of data (Clements et al., 2021).

In conclusion, it is becoming increasingly apparent that the effect of ocean "acidification" on marine biota has likely been exaggerated.

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Rae, J. & Burke, Andrea & Robinson, L. & Adkins, Jess & Chen, T. & Cole, C. & Greenop, R. & Li 李涛, Tao & Littley, E. & Nita, Dan & Stewart, J. & Taylor, B.. (2018). CO₂ storage and release in the deep Southern Ocean on millennial to centennial timescales. *Nature*. 562. <https://doi.org/10.1038/s41586-018-0614-0>

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Ridd, Peter & Silva, Eduardo & Stieglitz, Thomas. (2013). Have coral calcification rates slowed in the last twenty years?. *Marine Geology*. 346. 392–399. <https://doi.org/10.1016/j.margeo.2013.09.002>

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3. Ocean Acidification

4 Human influences on the climate

4.1 Components of radiative forcing and their history

4.1.1 Historical radiative forcing

A changing climate has been the norm throughout the Earth's 4.6-billion-year history. The Earth's temperature and weather patterns change naturally over timescales ranging from decades to millions of years. Natural variations in the surface climate originate in two ways. Internal climate fluctuations associated with circulations in the atmosphere and ocean produce exchanges of energy, water, and carbon between the atmosphere, oceans, land, and ice. External influences on the climate system include variations in the energy received from the sun and the effects of volcanic eruptions. Human activities influence climate through changing land use and land cover. Humans are also changing the composition of the atmosphere by increasing emissions of CO₂ and other greenhouse gases and by altering the concentrations of aerosol particles in the atmosphere.

The earth is warmed by the sunlight it absorbs and cooled by the radiative heat it emits to outer space. Averaged over Earth, each of these processes involve power flows of about 240 Watts per square meter (W/m²). When they are in balance, there are no net external causes of warming or cooling. Human (and some natural) influences on the climate alter this balance and so cause the climate to change.

Influences on the energy balance are quantified by "radiative forcing", the extent to which they disturb the warming/cooling balance; a positive forcing warms while a negative forcing cools. The IPCC's estimated history of major components of radiative forcing since 1750 is shown in the following two figures from the IPCC AR6.

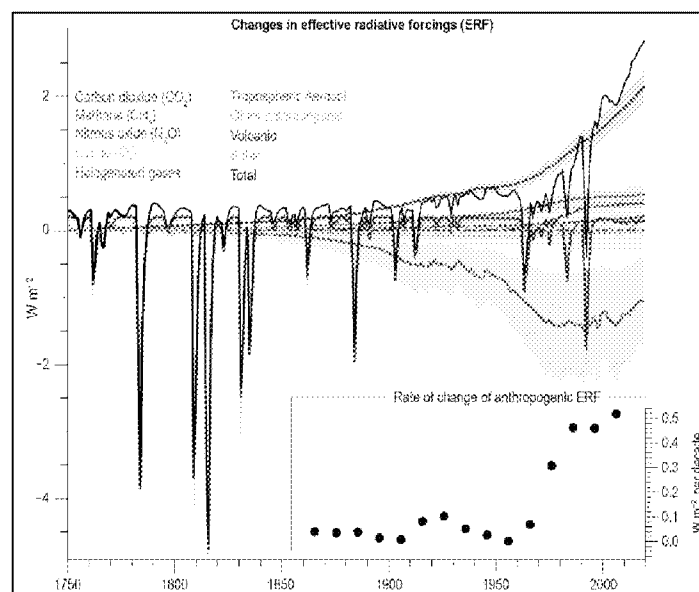


Figure 4.1.1: IPCC estimates of radiative forcing components over time. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-2/figure-2-10/>

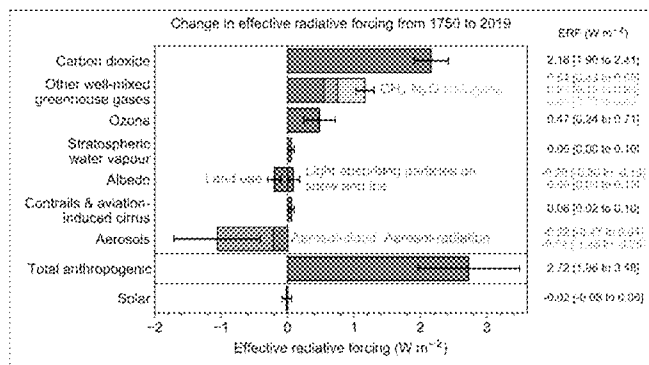


Figure 4.1.2 IPCC estimates of radiative forcing component changes from 1750 to 2019. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-7/figure-7-6/>

These graphs show that the total radiative forcing is comprised of natural and anthropogenic components. Carbon dioxide is the largest human influence on the climate and the one most relevant to the effects of energy-using systems like motor vehicles. It exerts a warming influence by decreasing the cooling power of the atmosphere. Emissions of CO₂ are accumulating in the atmosphere, as described in the following section, so that the warming influence is increasing. Other greenhouse gases (methane, nitrous oxide, halogens, and ozone), which act similarly, currently add another 75% to CO₂'s warming. Aerosols exert a cooling effect, although with large uncertainties in the way they catalyze the formation of reflective clouds. As a result, understanding of the causes of recent warming requires not just identifying the warming effects of CO₂, but also the more uncertain cooling effects of sulfate aerosols.

IS THIS PARA MORE RELEVANT TO RADIATIVE FORCING OR TO ATTRIBUTION CHAPTER The IPCC views the role of the sun as negligible, based on their preference for reconstructions that imply minimal solar change since preindustrial times. Connolly *et al.* (2021) reviewed sixteen different Total Solar Irradiance (TSI) reconstructions in the literature covering the 1600-2000 interval; they vary from almost no change in TSI to a relatively large upward trend. Connolly *et al.* point out that the variation in TSI reconstructions combined with variations in surface temperature reconstructions implies pairings can be found that are consistent with either no or most 20th century warming being attributable to the sun. A particularly thorny issue is the gap in the TSI data between 1989 and 1991 due to a delay in the launch of a monitor after the Space Shuttle Challenger disaster on January 28 1986, which prevented a replacement satellite from being launched in time to overlap with, and its readings to be intercalibrated with, the prior system

(Zacharias 2014, Scafetta et al. 2019). The question of whether there is an upward trend in TSI over 1978 to 2018 comes down to how the missing data in that gap are filled. ~~That being the case it is noteworthy that Zacharias (2014) observes the solar research community has been motivated by a desire to downplay any potential role of the sun in climate change so as not to detract from arguments for greenhouse gas abatement:~~ THIS IS DUPLICATIVE OF SOME OF THE MATERIAL I HAVE IN THE ATTRIBUTION CHAPTER.

~~A conclusive TSI time series is not only desirable from the perspective of the scientific community, but also when considering the rising interest of the public in questions related to climate change issues, thus preventing climate skeptics from taking advantage of these discrepancies within the TSI community by, e.g., putting forth a presumed solar effect as an excuse for inaction on anthropogenic warming.~~

~~(Zacharias 2014)~~

I'M NOT THRILLED WITH THE ZACHARIAS REF THIS SEEMS LIKE CHEAP POINTS SCORING, AND ATTRIBUTING MOTIVES TO OTHER PEOPLE IS A BAD MOVE. I THINK THE STATEMENT FROM CONNOLLY IS BETTER:

Connolly et al. (2023) found that the Sun/climate debate is an issue where the IPCC's consensus statements were prematurely achieved through the suppression of dissenting scientific opinions.

The other natural forcing component is largely volcanic aerosols, which exert an episodic cooling influence.

The anthropogenic forcing component was negligible before about 1900 and has increased steadily since, rising to almost 3 W/m² today. However, this is still only about 1 percent of the unperturbed radiation flows, making it a challenge to isolate the effects of anthropogenic forcing since state-of-the-art satellite estimates of global radiative energy flows are only accurate to a few W/m². Natural sources of global energy imbalance other than volcanoes are not included in these graphs because they remain largely unknown.

4.1.2 Future radiative forcing

Carbon dioxide's warming influence depends upon how much "extra" CO₂ accumulates in the atmosphere- i.e., its concentration. The CO₂ level as recorded at the Mauna Loa observatory in Hawaii is generally used as the representative global average concentration. The data are

available online at <https://gml.noaa.gov/ccgg/trends/index.html>. The concentration was about 316 ppm at the start of the record in 1959 and is now about 425 ppm, a 34 percent increase.

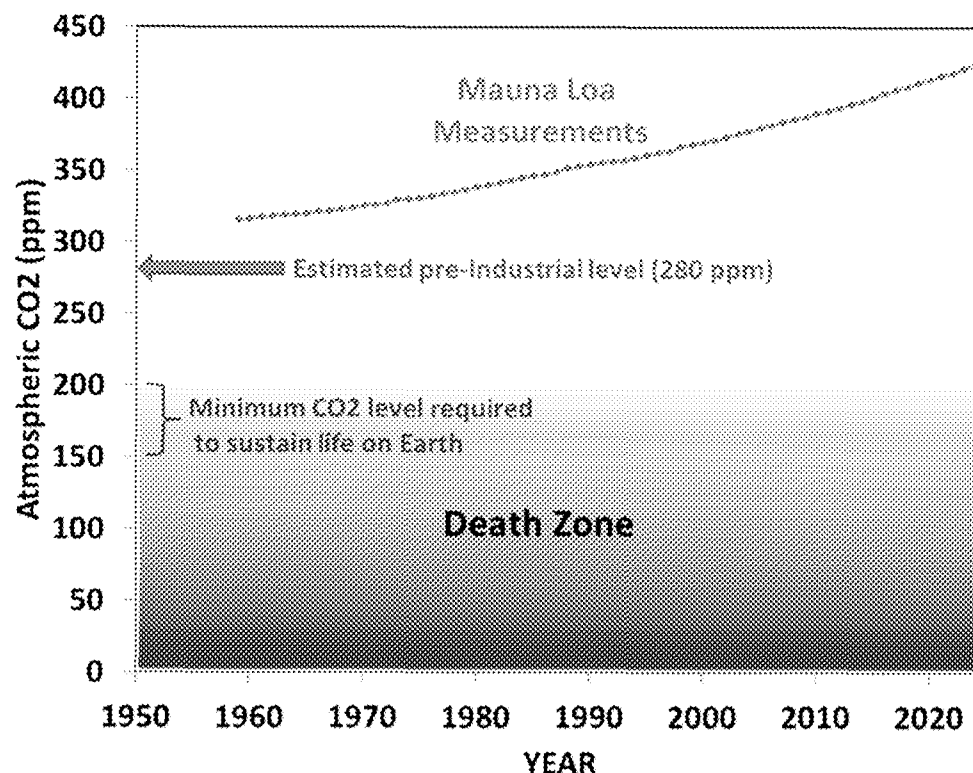


Fig. 4.1.3 Yearly average atmospheric CO₂ concentrations (1959-2024) measured at Mauna Loa, HI (green) compared to the estimated pre-Industrial CO₂ concentration of 280 ppm, and the estimated minimum levels required to sustain life on Earth (150 to 200 ppm). Need source

The annual increase in concentration is only about half of the CO₂ emitted because land and ocean processes absorb “excess” CO₂ at a rate approximately 50% of human emissions. Thus, future concentrations, and hence future human influences on the climate, depend upon two components: (1) future rates of global human CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere. We discuss each of these in turn.

4.2 Future emission scenarios and the carbon cycle

4.2.1 Emission scenarios

Assessing the future dangers of GHG emissions requires assumptions about what those emissions will be. Future emissions, and hence human influences on the climate, will depend upon future demographics, economic progress, regulation, and the energy and agricultural technologies in use. Various assumptions about each of those lead to projections of greenhouse gas emissions and concentrations, aerosol concentrations, and changes in land use, which ultimately can be combined into assumptions about anthropogenic radiative forcing.

Because of the great uncertainties about these many factors in the the decades to come, instead of making precise predictions of future concentrations, the IPCC has created various sets of scenarios meant to span a plausible range of possibilities for population, economy, technology, and so on. Recent versions of the scenarios are labeled by a number indicating the anthropogenic radiative forcing expected in 2100 under that scenario. Thus, a scenario labeled with a “6” corresponds to 6 W/m² of human-induced radiative forcing (warming) at the end of the century. (Recall current anthropogenic radiative forcing is about 2.7 W/m².)

Although the IPCC does not put its emission scenarios forward as forecasts they are often treated as such. Comparisons of past scenario groups against observations shows a tendency for IPCC emission projections to overstate actual subsequent emissions. For the IPCC Third and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* were used and hence were referred to as the SREP scenarios. McKittrick *et al.* (2012) showed that, when converted to per capita terms, the SREP scenario distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by the later analysis in Hausfather *et al.* (2019) who showed that observed atmospheric CO₂ concentrations tracked the low end of the SRES range.

For the Fifth Assessment Report the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCP). These were identified by a number representing the increase in forcing and were thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying a radiative forcing in 2100 of 2.6 W/m²) projects a GHG concentration pathway leading to warming well below 2 C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5 C warming just in this century.

RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario in both the academic literature and popular media. It was therefore used to generate the reference outcome supposedly representing the 21st century world in the absence of emission reduction policies. But RCP8.5 was intended as a low-probability high emissions scenario and its usage as a

business-as-usual baseline has been criticized as grossly misleading.¹ Hausfather and Peters (2020) writing in a commentary in *Nature* magazine, pointed out that RCP8.5 was developed as an extreme worst-case, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting:

RCP8.5 was intended to explore an unlikely high-risk future. But it has been widely used by some experts, policymakers and the media as something else entirely: as a likely ‘business as usual’ outcome. A sizeable portion of the literature on climate impacts refers to RCP8.5 as business as usual, implying that it is probable in the absence of stringent climate mitigation. The media then often amplifies this message, sometimes without communicating the nuances. This results in further confusion regarding probable emissions outcomes, because many climate researchers are not familiar with the details of these scenarios in the energy-modelling literature.

(Hausfather and Peters 2020)

The implausibility of the RCP8.5 scenario was examined by Burgess *et al.* (2021). They noted that RCP8.5 has already diverged from observed energy use trends, and the near future trends diverge sharply from those of the International Energy Agency (IEA) which provides market-based projections of energy use for coming decades. IEA trends are based on plausible extrapolations of current economic and demographic trends, and the results run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but even lower emission scenarios are looking unlikely. Burgess *et al.* comment (p. 8):

Beyond 2040, if the trends anticipated by energy agency forecasts continue, carbon intensity will continue diverging from AR5 and SSP baselines—especially from higher-emission scenarios such as RCP8.5, due to the assumptions about fossil-fuel expansion in these scenarios that are increasingly implausible.

Widespread use of RCP8.5 has created an alarmist bias in the climate impacts literature. The extent of this problem was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found (p. 32) that some 16,800 scientific papers published between 2010 and 2020 used the RCP8.5 scenario, with about 4,500 of the articles (p. 16) linking RCP8.5 with the concept of “business-as-usual”. Their analysis showed how RCP8.5 was misused not only by individual researchers, but also by influential science agencies like the IPCC and the US National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets. They offer the following example (p. 30):

¹ This extreme scenario is useful for modelers, since a large forcing generates a large response (warming) making it easier to assess a model’s sensitivity. But that’s very different than claiming it is a plausible future.

The USNCA employed RCP8.5 as a baseline scenario, despite warning against such use, and compared it to RCP4.5 throughout its report to generate quantitative economic estimates of the benefits of mitigation. In a front-page story, the *New York Times* promoted the report's misuse of RCP8.5 as a baseline scenario:

"A major scientific report issued by 13 federal agencies on Friday presents the starkest warnings to date of the consequences of climate change for the United States, predicting that if significant steps are not taken to rein in global warming, the damage will knock as much as 10 percent off the size of the American economy by century's end."

Pielke and Ritchie (2020) reported new studies using RCP8.5 were appearing in the literature at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and "business as usual." They conclude (p. 34) that the climate research community has spent a decade "committing scientific resources to science fiction" (emphasis added):

"Derived estimates from RCP8.5 as "business as usual" such as future climate impacts, the impacts avoided from mitigation and the cost effectiveness and benefits of mitigation have no real-world meaning... **The scientific literature has become imbalanced in an apocalyptic direction.**

(Pielke Jr. and Ritchie p. 34)

The IPCC later converted the RCP scenarios to the "Shared Socioeconomic Pathway" or SSP scenarios, but these have continued the pattern of bias shown with the RCP and SRES scenarios. Figure 3.1.4 was generated using the Resources for the Future Global Energy Outlook tool (RFF 2025). The black line shows total global observed CO₂ emissions compiled by the International Energy Agency (IEA). The solid green line is the emission trajectory developed by BP Energy taking account of current emission control policies and global energy use outlooks. It overlaps a solid black line which represents the emission projection from the IEA also taking account of energy use projections and current policies. The dashed lines show the range of IPCC SSP policies. As of 2023 global CO₂ emissions have been tracking well below the SSP scenarios especially the two highest ones (SSP5-8.5 and SSP3-7.0).

Carbon dioxide emissions (Million metric tons), by Outlooks & Scenarios. Filtered by Region: World; Fuel: All; Outlook: 2023 Shell (Sky 2050).

Source: RFF Global Energy Outlook at www.rff.org/geo

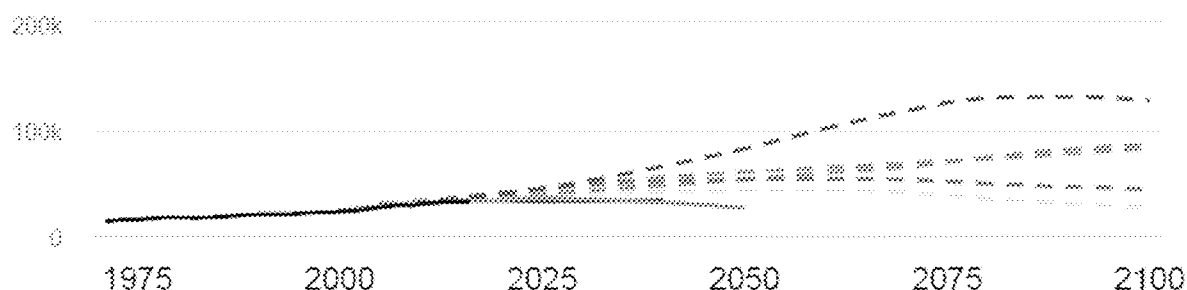


Figure 4.2.1. Observed and projected CO₂ emissions. Source: RFF (2025).

4.2.2 The carbon cycle relating emissions and concentrations

Global carbon cycle models relate concentrations to emissions using estimates of various land and ocean processes that remove CO₂ from, and emit CO₂ into, the atmosphere. Our understanding of these processes was reviewed by Crisp et al. (2021). The natural fluxes of CO₂ in and out of the Earth's surface are very large, many times anthropogenic emissions, but those CO₂ sources and sinks were assumed to be in approximate balance in pre-Industrial times, as evidenced by relatively constant levels of atmospheric CO₂ in centuries past derived from air bubbles in ice cores. This is one of several reasons why increasing atmospheric CO₂ levels are believed to be dominated by anthropogenic sources.

Specifically, fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) has led to steadily increasing CO₂ levels in the atmosphere, as shown in Fig. 1.2.1. CO₂ emissions from fossil fuel burning is a small fraction of the natural carbon cycle components. About 44,000 Gigatonnes of carbon-equivalent (GtC) are stored in the atmosphere and oceans, mostly in the form of CO₂. (Ciais et al. 2013). Between 150 and 200 GtC are released naturally each year through oceanic outgassing and land-based processes like plant decay and animal respiration. A variable but roughly equivalent amount is absorbed each year by the land and oceans, with a small net loss from the atmosphere because the formation of deep ocean sediment sequesters some carbon permanently. Global fossil fuel consumption and cement manufacture released about 10.3 GtC in 2023, up from 6.2 GtC in 1990 (Ritchie et al.

2024). Of this, about half is naturally sequestered through plant growth and oceanic uptake while the remainder, about half, adds to the atmospheric stock (Ciais et al. 2013).

As noted, each year natural processes remove a net amount of CO₂ equivalent to about 50% of global emissions. Thus, anthropogenic CO₂ emissions average twice what is required to explain the atmospheric rise in CO₂ concentration. The near-constancy of that 50% fraction (the “airborne fraction”) also means that the more CO₂ humanity produces, the faster Nature removes it from the atmosphere. That 50% fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Nino, La Nina, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert et al., 2004).

The main processes which remove excess CO₂ from the atmosphere are increased production of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein et al., 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon observed by satellites since monitoring of global greenness began in the 1982. This greening has been traced to CO₂ fertilization and greater drought tolerance of plants exposed to elevated CO₂ levels. While there had been some uncertainty whether a greening trend continued beyond 2000, the most recent research (Chen et al., 2023) has shown continued greening, with even some slight acceleration since 2000. Global greening is discussed further in Section 3.1.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be reliably measured. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp et al. (2021).

Public policy can only change the rate of emissions, not the concentration in the atmosphere. For criteria air contaminants the rate and concentration are closely connected because the lifetime is short and the concentration is small. When emissions are reduced the local pollution concentration drops rapidly, usually on a time scale of a few days. Not so with the global average CO₂ concentration since global carbon cycle is vast and slow. A change in local emissions today will only have a very small global effect, and only after a long time lag. After a pulse (release) of CO₂ emissions to the atmosphere only about 40 percent ($\pm 15\%$) of the extra CO₂ will have been sequestered after twenty years. After a thousand years about 75 percent ($\pm 10\%$) will have been sequestered, and the remainder will gradually be removed over the ensuing tens of thousands of years (Ciais et al. 2013, pp. 472-473). Consequently US CO₂ emission reductions will take decades or centuries to lead to a reduction in the global CO₂ concentration.

To reduce the atmospheric stock of CO₂, assuming the entire increase is anthropogenic, would require emissions to fall below the natural sequestration rate. Since that rate has been averaging about 50% of emissions, a reduction of global emissions by 50% would (at least temporarily) halt the rise in atmospheric CO₂. The 1997 Kyoto Protocol proposed to cap industrial nations' CO₂ emissions at a modest five percent below 1990 levels by the year 2012. Even though this policy ended up being too costly for most nations to implement, full compliance would not have substantially reduced atmospheric CO₂ levels. It would only have slightly slowed CO₂ growth, reaching the projected 2100 level in 2105 instead (Wigley 1998). Similarly, Lomborg (2016) used the widely-used MAGICC climate model and showed that full compliance with the Paris Accord would not stop warming, it would only prevent about 0.1C warming and delay hitting the baseline year 2100 temperature levels by about a decade.

Thus, in contrast with conventional air pollution control, local actions yield extremely small local effects, and only after a long time lag. The practice of referring to unilateral US reductions as “combatting climate change” or “taking action on climate” reflects a profound misunderstanding of the scale of the issue. The scale problem is compounded by recognizing that US motor vehicles account only for about 4 percent of global CO₂ emissions so even a fifty percent reduction in those emissions would have a vanishingly small effect on the global climate.

4.3 Aerosols and the uncertainties associated with them

The role of this chapter should be to address radiative forcing – not ECS or warming attribution. I think that the material in this section should be moved to ECS or attribution. There is huge uncertainty in the aerosol indirect effect, which relates directly to radiative forcing. I can write up something on this

THIS PARA SHOULD BE DELETED HERE, THIS IS COVERED IN THE ATTRIBUTION CHAPTER The climate's sensitivity to CO₂ (as quantified by ECS, the Equilibrium Climate Sensitivity²) is uncertain in part because the anthropogenic radiative forcing is ~~uncertain because the net forcing~~ results from (at least) two counteracting components: warming from GHG's and cooling from aerosols. The observed warming can therefore be made to be consistent with a wide range of pairs of these forces. In the following schematic, the net warming represented by the red

² ECS is formally defined as the increase in equilibrium global average surface temperature resulting from a doubling of the atmospheric CO₂ concentration above its pre-industrial value of 280 ppm. Estimates of ECS are reviewed in Section XX.

arrow could be due to the High GHG warming/strong aerosol cooling pair, or the Low GHG warming/weak aerosol cooling pair, or something in between.

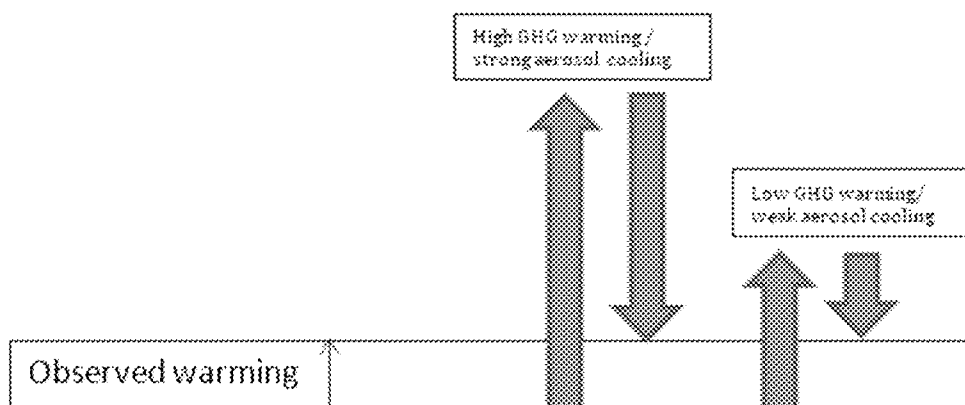


Figure 4.3.1: High and low climate sensitivity to GHGs can be reconciled with the same warming by assuming an offsetting aerosol cooling effect.

THIS CAN GO IN ECS CHAPTER Research on the strength of aerosol cooling is therefore central to more precise ECS estimates. Lewis and Curry (2018) note that after the IPCC AR5 was published in 2013, eleven studies appeared in the scientific literature all finding that aerosol cooling was weaker than had previously been conjectured. Combining the updated aerosol estimates with greenhouse gas, ocean heat uptake and atmospheric warming data from the IPCC and applying standard empirical methods, Lewis and Curry (2018) estimated the best-guess ECS to be 1.66°C with a 95 percent uncertainty range of 1.15 °C – 2.7°C. They concluded that based on the ECS values derived from most IPCC climate models were incompatible with observed data.

There has been further evidence of lower aerosol cooling (implying lower ECS) such as Liu et al. (2021). THIS COULD BE MADE TO BE RELEVANT TO RADIATIVE FORCING CHAPTER These authors tested the hypothesis that aerosols from wildfires has increased since before the 20th century which, if true, would mean there had to have been relatively strong CO₂ warming over that period offsetting the aerosol cooling. They examined soot layers in ice cores extracted from Antarctica and South America and determined that wildfire activity prior to the 20th century was higher than previously believed. Instead of wildfire activity rising steadily from the 1700s to the present, it was high all the time, thus contradicting the hypothesized aerosol cooling trend in

the Southern Hemisphere during the 20th century. They pointed out how this finding relates to the climate sensitivity issue:

Accurate estimates of aerosol radiative forcing are also crucial for better understanding the transient climate response (TCR) and equilibrium climate sensitivity (ECS) to increasing CO₂ and more accurate projection of future climate change. The negative aerosol radiative forcing can, in part, cancel out the positive forcing of increasing greenhouse gases and contribute to the uncertainty of total radiative forcing. An overly large aerosol cooling implies that models might overestimate TCR and ECS to reproduce historical temperature response. A recent study using one of the latest-generation CMIP6 climate models (E3SM) suggested that reducing both the magnitudes of negative aerosol radiative forcing and climate sensitivity yields a better agreement with the observed historical record of the surface temperature.

(Liu et al. 2021)

~~Liu told the UK Daily Mail³~~

~~Climate scientists have known that the most recent generation of climate models have been over-estimating surface temperature sensitivity to greenhouse gasses, but we haven't known why or by how much. This research offers a possible explanation.~~

I really think we should limit direct quotes to IPCC or other official docs, or something that is especially profound.

More evidence pointing to weak aerosol cooling was reported by Wang *et al.* (2021). They noted that the strength of aerosol cooling is partly mediated by cloud behavior and differs between the North and South Hemispheres because of the different density of aerosol emissions. This allowed them to construct another test of climate model validity, which came out in favor of low ECS models. In their words:

Since anthropogenic aerosols primarily concentrate in the Northern Hemisphere, strong aerosol-cloud interaction models produce an interhemispheric asymmetric warming. We show that the observed warming asymmetry during the mid to late 20th century is more consistent with low ECS (weak aerosol indirect effect) models. PARAPHRASE, DIRECT QUOTE NOT NEEDED

Wang et al. (2021)

³ Available online at <https://www.dailymail.co.uk/sciencetech/article-9629919/Climate-change-warming-effect-greenhouse-gases-overestimated-ice-core-study-suggests.html>

THIS PARA IS AN ATTRIBUTION STATEMENT, NOT A FORCING STATEMENT To summarize, quantifying warming due to CO₂ requires understanding the strength of aerosol cooling. While that latter is uncertain a substantial body of recent evidence points to it being relatively weak, implying that CO₂ warming is likewise weak.

Summary

- The global climate is naturally variable. Anthropogenic CO₂ emissions add to that variability by changing the total radiative balance in the atmosphere.
- The IPCC has downplayed the role of the sun in climate change but there are Total Solar Irradiance reconstructions that imply it might have been important, and the modern record is uncertain due to an interruption in satellite coverage.
- Projections of anthropogenic emissions are combined with carbon cycle model estimates of atmospheric CO₂ removal to estimate future CO₂ concentrations and hence the radiative forcings. These are input to climate models to estimate future anthropogenic changes in the climate.
- IPCC emission scenarios envelopes have tended to exceed observed trends.
- The vast majority of academic climate “impacts” studies in recent years are based upon the extreme RCP8.5 scenario that is considered implausible; its usage as a business-as-usual scenario is misleading.
- Despite ample evidence that scenario envelopes are exaggerated, and despite criticism of this practice in the peer-reviewed literature, the IPCC’s most recent scenario set (SSP) perpetuates this malpractice.
- The global carbon cycle heavily dampens the effect of changes in local (e.g. U.S.) CO₂ emissions. Even global-scale emission reductions will have only small, much delayed effects.
- ~~Knowing the magnitude of CO₂ warming requires knowing the strength of aerosol cooling. While that is uncertain, a substantial body of recent evidence points to it being relatively weak, implying CO₂ warming is likewise weak. THIS IS AN ATTRIBUTION STATEMENT~~

Scaffeta, Nicola, Richard C. Willson, Jae N. Lee and Dong Wu (2019) Modeling Quiet Solar Luminosity Variability from TSI Satellite Measurements and Proxy Models during 1980–2018. *Remote Sensing* 11(21) 2569 <https://doi.org/10.3390/rs11212569>

Connolly, Roman, Willie Soon, Michael Connolly et al. (2021) How much has the Sun influenced Northern Hemisphere temperature trends? An ongoing debate *Research in Astronomy and Astrophysics* 21(6) doi: 10.1088/1674-4527/21/6/131 <https://iopscience.iop.org/article/10.1088/1674-4527/21/6/131>

Zacharias, Pia (2014) An Independent Review of Existing Total Solar Irradiance Records. *Surveys in Geophysics* 35 pp. 897—912 <https://link.springer.com/article/10.1007/s10712-014-9294-y>

Liu, Pengfei et al. (2021) “Improved estimates of preindustrial biomass burning reduce the magnitude of aerosol climate forcing in the Southern Hemisphere” *Science Advances* 7(22) May 2021 <https://doi.org/10.1126/sciadv.abc1379>

Wang, C., Soden, B. J., Yang, W., & Vecchi, G. A. (2021). Compensation between cloud feedback and aerosol-cloud interaction in CMIP6 models. *Geophysical Research Letters*, 48, e2020GL091024. <https://doi.org/10.1029/2020GL091024>

4 Human influences on the climate

4.1 Components of radiative forcing and their history

4.1.1 Historical radiative forcing

A changing climate has been the norm throughout the Earth's 4.6-billion-year history. The Earth's temperature and weather patterns change naturally over timescales ranging from decades to millions of years. Natural variations in the surface climate originate in two ways. Internal climate fluctuations associated with circulations in the atmosphere and ocean produce exchanges of energy, water, and carbon between the atmosphere, oceans, land, and ice. External influences on the climate system include variations in the energy received from the sun and the effects of volcanic eruptions. Human activities influence climate through changing land use and land cover. Humans are also changing the composition of the atmosphere by increasing emissions of CO₂ and other greenhouse gases and by altering the concentrations of aerosol particles in the atmosphere.

The earth is warmed by the sunlight it absorbs and cooled by the radiative heat it emits to outer space. Averaged over Earth, each of these processes involve power flows of about 240 Watts per square meter (W/m²). When they are in balance, there are no net external causes of warming or cooling. Human (and some natural) influences on the climate alter this balance and so cause the climate to change.

Influences on the energy balance are quantified by “radiative forcing”, the extent to which they disturb the warming/cooling balance; a positive forcing warms while a negative forcing cools. The IPCC's estimated history of major components of radiative forcing since 1750 is shown in the following two figures from the IPCC AR6.

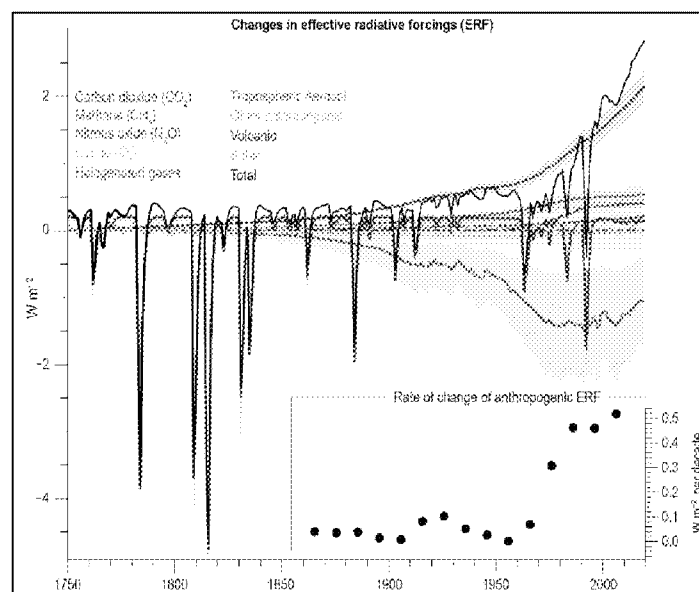


Figure 4.1.1: IPCC estimates of radiative forcing components over time. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-2/figure-2-10/>

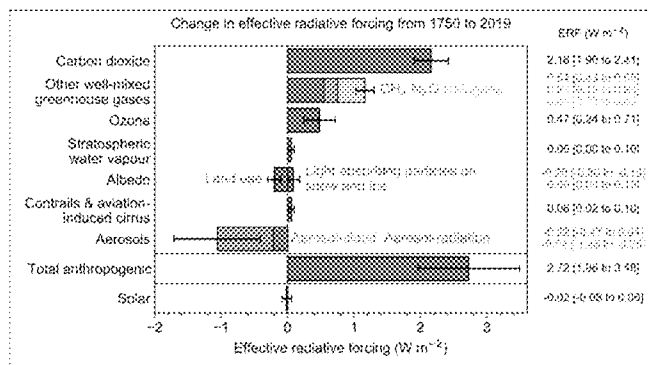


Figure 4.1.2 IPCC estimates of radiative forcing component changes from 1750 to 2019. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-7/figure-7-6/>

These graphs show that the total radiative forcing is comprised of natural and anthropogenic components. Carbon dioxide is the largest human influence on the climate and the one most relevant to the effects of energy-using systems like motor vehicles. It exerts a warming influence by decreasing the cooling power of the atmosphere. Emissions of CO₂ are accumulating in the atmosphere, as described in the following section, so that the warming influence is increasing. Other greenhouse gases (methane, nitrous oxide, halogens, and ozone), which act similarly, currently add another 75% to CO₂'s warming. Aerosols exert a cooling effect, although with large uncertainties in the way they catalyze the formation of reflective clouds. As a result, understanding of the causes of recent warming requires not just identifying the warming effects of CO₂, but also the more uncertain cooling effects of sulfate aerosols.

The IPCC views the role of the sun as negligible, based on their preference for reconstructions that imply minimal solar change since preindustrial times. Connolly *et al.* (2021) reviewed sixteen different Total Solar Irradiance (TSI) reconstructions in the literature covering the 1600-2000 interval; they vary from almost no change in TSI to a relatively large upward trend. Connolly *et al.* point out that the variation in TSI reconstructions combined with variations in surface temperature reconstructions implies pairings can be found that are consistent with either no or most 20th century warming being attributable to the sun. A particularly thorny issue is the gap in the TSI data between 1989 and 1991 due to a delay in the launch of a monitor after the Space Shuttle Challenger disaster on January 28 1986, which prevented a replacement satellite from being launched in time to overlap with, and its readings to be intercalibrated with, the prior system (Zacharias 2014, Scafetta et al. 2019). The question of whether there is an upward trend

in TSI over 1978 to 2018 comes down to how the missing data in that gap are filled. That being the case it is noteworthy that Zacharias (2014) observes the solar research community has been motivated by a desire to downplay any potential role of the sun in climate change so as not to detract from arguments for greenhouse gas abatement:

A conclusive TSI time series is not only desirable from the perspective of the scientific community, but also when considering the rising interest of the public in questions related to climate change issues, thus preventing climate skeptics from taking advantage of these discrepancies within the TSI community by, e.g., putting forth a presumed solar effect as an excuse for inaction on anthropogenic warming.

(Zacharias 2014)

The other natural forcing component is largely volcanic aerosols, which exert an episodic cooling influence.

The anthropogenic forcing component was negligible before about 1900 and has increased steadily since, rising to almost 3 W/m² today. However, this is still only about 1 percent of the unperturbed radiation flows, making it a challenge to isolate the effects of anthropogenic forcing since state-of-the-art satellite estimates of global radiative energy flows are only accurate to a few W/m². Natural sources of global energy imbalance other than volcanoes are not included in these graphs because they remain largely unknown.

4.1.2 Future radiative forcing

Carbon dioxide's warming influence depends upon how much "extra" CO₂ accumulates in the atmosphere- i.e., its concentration. The CO₂ level as recorded at the Mauna Loa observatory in Hawaii is generally used as the representative global average concentration. The data are available online at <https://gml.noaa.gov/ccgg/trends/index.html>. The concentration was about 316 ppm at the start of the record in 1959 and is now about 425 ppm, a 34 percent increase.

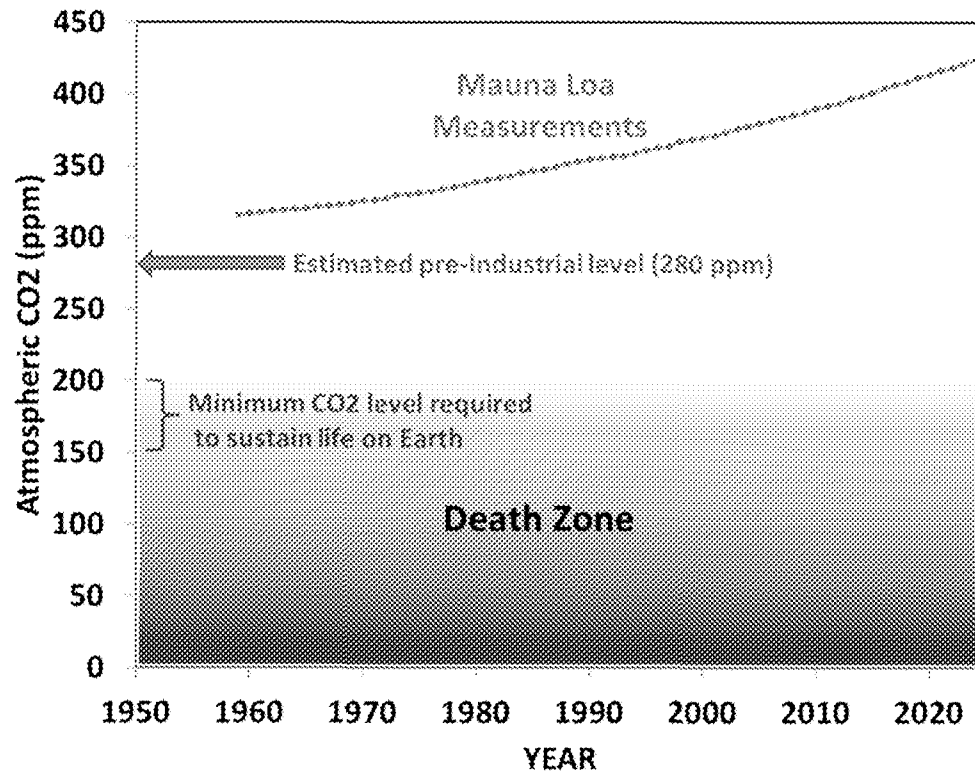


Fig. 4.1.3 Yearly average atmospheric CO₂ concentrations (1959-2024) measured at Mauna Loa, HI (green) compared to the estimated pre-Industrial CO₂ concentration of 280 ppm, and the estimated minimum levels required to sustain life on Earth (150 to 200 ppm). Need source

The annual increase in concentration is only about half of the CO₂ emitted because land and ocean processes absorb “excess” CO₂ at a rate approximately 50% of human emissions. Thus, future concentrations, and hence future human influences on the climate, depend upon two components: (1) future rates of global human CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere. We discuss each of these in turn.

4.2 Future emission scenarios and the carbon cycle

4.2.1 Emission scenarios

Assessing the future dangers of GHG emissions requires assumptions about what those emissions will be. Future emissions, and hence human influences on the climate, will depend upon future

demographics, economic progress, regulation, and the energy and agricultural technologies in use. Various assumptions about each of those lead to projections of greenhouse gas emissions and concentrations, aerosol concentrations, and changes in land use, which ultimately can be combined into assumptions about anthropogenic radiative forcing.

Because of the great uncertainties about these many factors in the decades to come, instead of making precise predictions of future concentrations, the IPCC has created various sets of scenarios meant to span a plausible range of possibilities for population, economy, technology, and so on. Recent versions of the scenarios are labeled by a number indicating the anthropogenic radiative forcing expected in 2100 under that scenario. Thus, a scenario labeled with a “6” corresponds to 6 W/m² of human-induced radiative forcing (warming) at the end of the century. (Recall current anthropogenic radiative forcing is about 2.7 W/m².)

Although the IPCC does not put its emission scenarios forward as forecasts they are often treated as such. Comparisons of past scenario groups against observations shows a tendency for IPCC emission projections to overstate actual subsequent emissions. For the IPCC Third and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* were used and hence were referred to as the SREP scenarios. McKittrick *et al.* (2012) showed that, when converted to per capita terms, the SREP scenario distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by the later analysis in Hausfather *et al.* (2019) who showed that observed atmospheric CO₂ concentrations tracked the low end of the SRES range.

For the Fifth Assessment Report the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCP). These were identified by a number representing the increase in forcing and were thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying a radiative forcing in 2100 of 2.6 W/m²) projects a GHG concentration pathway leading to warming well below 2 C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5 C warming just in this century.

RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario in both the academic literature and popular media. It was therefore used to generate the reference outcome supposedly representing the 21st century world in the absence of emission reduction policies. But RCP8.5 was intended as a low-probability high emissions scenario and its usage as a business-as-usual baseline has been criticized as grossly misleading.¹ Hausfather and Peters (2020) writing in a commentary in *Nature* magazine, pointed out that RCP8.5 was developed as

¹ This extreme scenario is useful for modelers, since a large forcing generates a large response (warming) making it easier to assess a model’s sensitivity. But that’s very different than claiming it is a plausible future.

an extreme worst-case, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting:

RCP8.5 was intended to explore an unlikely high-risk future. But it has been widely used by some experts, policymakers and the media as something else entirely: as a likely ‘business as usual’ outcome. A sizeable portion of the literature on climate impacts refers to RCP8.5 as business as usual, implying that it is probable in the absence of stringent climate mitigation. The media then often amplifies this message, sometimes without communicating the nuances. This results in further confusion regarding probable emissions outcomes, because many climate researchers are not familiar with the details of these scenarios in the energy-modelling literature.

(Hausfather and Peters 2020)

The implausibility of the RCP8.5 scenario was examined by Burgess *et al.* (2021). They noted that RCP8.5 has already diverged from observed energy use trends, and the near future trends diverge sharply from those of the International Energy Agency (IEA) which provides market-based projections of energy use for coming decades. IEA trends are based on plausible extrapolations of current economic and demographic trends, and the results run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but even lower emission scenarios are looking unlikely. Burgess *et al.* comment (p. 8):

Beyond 2040, if the trends anticipated by energy agency forecasts continue, carbon intensity will continue diverging from AR5 and SSP baselines—especially from higher-emission scenarios such as RCP8.5, due to the assumptions about fossil-fuel expansion in these scenarios that are increasingly implausible.

Widespread use of RCP8.5 has created an alarmist bias in the climate impacts literature. The extent of this problem was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found (p. 32) that some 16,800 scientific papers published between 2010 and 2020 used the RCP8.5 scenario, with about 4,500 of the articles (p. 16) linking RCP8.5 with the concept of “business-as-usual”. Their analysis showed how RCP8.5 was misused not only by individual researchers, but also by influential science agencies like the IPCC and the US National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets. They offer the following example (p. 30):

The USNCA employed RCP8.5 as a baseline scenario, despite warning against such use, and compared it to RCP4.5 throughout its report to generate quantitative economic estimates of the benefits of mitigation. In a front-page story, the *New York Times* promoted the report’s misuse of RCP8.5 as a baseline scenario:

“A major scientific report issued by 13 federal agencies on Friday presents the starkest warnings to date of the consequences of climate change for the United States, predicting that if significant steps are not taken to rein in global warming, the damage will knock as much as 10 percent off the size of the American economy by century’s end.”

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The IPCC later converted the RCP scenarios to the “Shared Socioeconomic Pathway” or SSP scenarios, but these have continued the pattern of bias shown with the RCP and SRES scenarios. Figure 3.1.4 was generated using the Resources for the Future Global Energy Outlook tool (RFF 2025). The black line shows total global observed CO₂ emissions compiled by the International Energy Agency (IEA). The solid green line is the emission trajectory developed by BP Energy taking account of current emission control policies and global energy use outlooks. It overlaps a solid black line which represents the emission projection from the IEA also taking account of energy use projections and current policies. The dashed lines show the range of IPCC SSP policies. As of 2023 global CO₂ emissions have been tracking well below the SSP scenarios especially the two highest ones (SSP5-8.5 and SSP3-7.0).

Carbon dioxide emissions (Million metric tons), by Outlooks & Scenarios. Filtered by Region: World; Fuel: All; Outlook: 2023 Shell (Sky 2050).

Source: RFF Global Energy Outlook at www.rff.org/geo

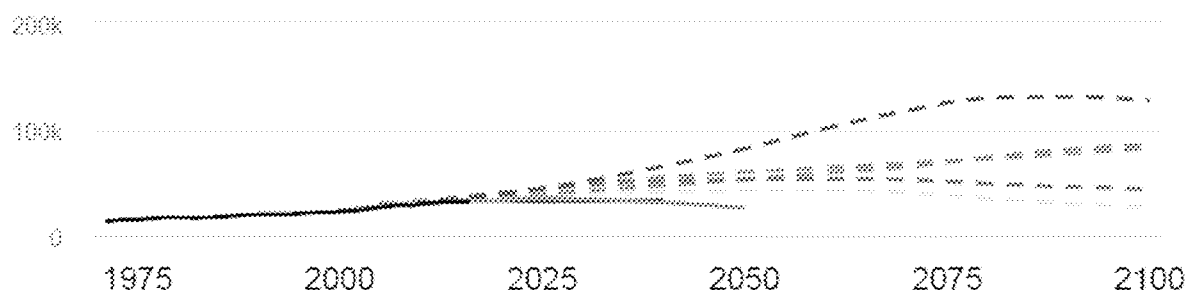


Figure 4.2.1. Observed and projected CO₂ emissions. Source: RFF (2025).

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Specifically, fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) has led to steadily increasing CO₂ levels in the atmosphere, as shown in Fig. 1.2.1. CO₂ emissions from fossil fuel burning is a small fraction of the natural carbon cycle components. About 44,000 Gigatonnes of carbon-equivalent (GtC) are stored in the atmosphere and oceans, mostly in the form of CO₂. (Ciais et al. 2013). Between 150 and 200 GtC are released naturally each year through oceanic outgassing and land-based processes like plant decay and animal respiration. A variable but roughly equivalent amount is absorbed each year by the land and oceans, with a small net loss from the atmosphere because the formation of deep ocean sediment sequesters some carbon permanently. Global fossil fuel consumption and cement manufacture released about 10.3 GtC in 2023, up from 6.2 GtC in 1990 (Ritchie et al.

2024). Of this, about half is naturally sequestered through plant growth and oceanic uptake while the remainder, about half, adds to the atmospheric stock (Ciais et al. 2013).

As noted, each year natural processes remove a net amount of CO₂ equivalent to about 50% of global emissions. Thus, anthropogenic CO₂ emissions average twice what is required to explain the atmospheric rise in CO₂ concentration. The near-constancy of that 50% fraction (the “airborne fraction”) also means that the more CO₂ humanity produces, the faster nature removes it from the atmosphere. That 50% fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Nino, La Nina, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert et al., 2004).

The main processes which remove excess CO₂ from the atmosphere are increased production of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein et al., 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon observed by satellites since monitoring of global greenness began in the 1982. This greening has been traced to CO₂ fertilization and greater drought tolerance of plants exposed to elevated CO₂ levels. While there had been some uncertainty whether a greening trend continued beyond 2000, the most recent research (Chen et al., 2023) has shown continued greening, with even some slight acceleration since 2000. Global greening is discussed further in Section 3.1.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be reliably measured. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp et al. (2021).

Public policy can only change the rate of emissions, not the concentration in the atmosphere. For criteria air contaminants the rate and concentration are closely connected because the lifetime is short and the concentration is small. When emissions are reduced the local pollution concentration drops rapidly, usually on a time scale of a few days. Not so with the global average CO₂ concentration since global carbon cycle is vast and slow. A change in local emissions today will only have a very small global effect, and only after a long time lag. After a pulse (release) of CO₂ emissions to the atmosphere only about 40 percent ($\pm 15\%$) of the extra CO₂ will have been sequestered after twenty years. After a thousand years about 75 percent ($\pm 10\%$) will have been sequestered, and the remainder will gradually be removed over the ensuing tens of thousands of years (Ciais et al. 2013, pp. 472-473). Consequently US CO₂ emission reductions will take decades or centuries to lead to a reduction in the global CO₂ concentration.

To reduce the atmospheric stock of CO₂, assuming the entire increase is anthropogenic, would require emissions to fall below the natural sequestration rate. Since that rate has been averaging about 50% of emissions, a reduction of global emissions by 50% would (at least temporarily) halt the rise in atmospheric CO₂. The 1997 Kyoto Protocol proposed to cap industrial nations' CO₂ emissions at a modest five percent below 1990 levels by the year 2012. Even though this policy ended up too costly for most nations to implement, full compliance would not have substantially reduced atmospheric CO₂ levels. It would only have slightly slowed CO₂ growth, reaching the projected 2100 level in 2105 instead (Wigley 1998). Similarly, Lomborg (2016) used the widely-used MAGICC climate model and showed that full compliance with the Paris Accord would not stop warming, it would only prevent about 0.1C warming and delay hitting the baseline year 2100 temperature levels by about a decade.

Thus, in contrast with conventional air pollution control, local actions yield extremely small local effects, and only after a long time lag. The practice of referring to unilateral US reductions as “combatting climate change” or “taking action on climate” reflects a profound misunderstanding of the scale of the issue. As will be discussed in Chapter 14, the scale problem is compounded by recognizing that US motor vehicles account only for about 4 percent of global CO₂ emissions so even a fifty percent reduction in those emissions would have a vanishingly small effect on the global climate.

4.3 Aerosols and the uncertainties associated with them

The climate's sensitivity to CO₂ (as quantified by ECS, the Equilibrium Climate Sensitivity²) is uncertain because the net forcing results from (at least) two counteracting components: warming from GHG's and cooling from aerosols. The observed warming can therefore be made to be consistent with a wide range of pairs of these forces. In the following schematic, the net warming represented by the red arrow could be due to the High GHG warming/strong aerosol cooling pair, or the Low GHG warming/weak aerosol cooling pair, or something in between.

² ECS is formally defined as the increase in equilibrium global average surface temperature resulting from a doubling of the atmospheric CO₂ concentration above its pre-industrial value of 280 ppm. Estimates of ECS are reviewed in Section XX.

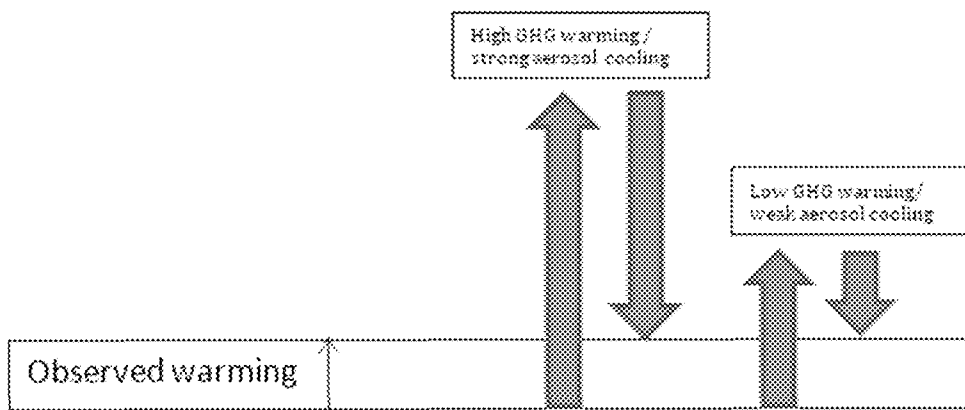


Figure 4.3.1: High and low climate sensitivity to GHGs can be reconciled with the same warming by assuming an offsetting aerosol cooling effect.

Research on the strength of aerosol cooling is therefore central to more precise ECS estimates. Lewis and Curry (2018) note that after the IPCC AR5 was published in 2013, eleven studies appeared in the scientific literature all finding that aerosol cooling was weaker than had previously been conjectured. Combining the updated aerosol estimates with greenhouse gas, ocean heat uptake and atmospheric warming data from the IPCC and applying standard empirical methods, Lewis and Curry (2018) estimated the best-guess ECS to be 1.66°C with a 95 percent uncertainty range of 1.15 °C – 2.7°C. They concluded that based on the ECS values derived from most IPCC climate models were incompatible with observed data.

There has been further evidence of lower aerosol cooling (implying lower ECS) such as Liu et al. (2021). These authors tested the hypothesis that aerosols from wildfires has increased since before the 20th century which, if true, would mean there had to have been relatively strong CO₂ warming over that period offsetting the aerosol cooling. They examined soot layers in ice cores extracted from Antarctica and South America and determined that wildfire activity prior to the 20th century was higher than previously believed. Instead of wildfire activity rising steadily from the 1700s to the present, it was high all the time, thus contradicting the hypothesized aerosol cooling trend in the Southern Hemisphere during the 20th century. They pointed out how this finding relates to the climate sensitivity issue:

Accurate estimates of aerosol radiative forcing are also crucial for better understanding the transient climate response (TCR) and equilibrium climate sensitivity (ECS) to increasing CO₂ and more accurate projection of future climate change. The negative aerosol radiative forcing can, in part, cancel out the positive forcing of increasing greenhouse gases and contribute to the uncertainty of total radiative forcing. An overly

large aerosol cooling implies that models might overestimate TCR and ECS to reproduce historical temperature response. A recent study using one of the latest-generation CMIP6 climate models (E3SM) suggested that reducing both the magnitudes of negative aerosol radiative forcing and climate sensitivity yields a better agreement with the observed historical record of the surface temperature.

(Liu et al. 2021)

Liu told the UK Daily Mail³

Climate scientists have known that the most recent generation of climate models have been over-estimating surface temperature sensitivity to greenhouse gasses, but we haven't known why or by how much. This research offers a possible explanation.

More evidence pointing to weak aerosol cooling was reported by Wang *et al.* (2021). They noted that the strength of aerosol cooling is partly mediated by cloud behavior and differs between the North and South Hemispheres because of the different density of aerosol emissions. This allowed them to construct another test of climate model validity, which came out in favor of low ECS models. In their words:

Since anthropogenic aerosols primarily concentrate in the Northern Hemisphere, strong aerosol-cloud interaction models produce an interhemispheric asymmetric warming. We show that the observed warming asymmetry during the mid to late 20th century is more consistent with low ECS (weak aerosol indirect effect) models.

Wang et al. (2021)

To summarize, quantifying warming due to CO₂ requires understanding the strength of aerosol cooling. While that latter is uncertain a substantial body of recent evidence points to it being relatively weak, implying that CO₂ warming is likewise weak.

Summary

³ Available online at <https://www.dailymail.co.uk/sciencetech/article-9629919/Climate-change-warming-effect-greenhouse-gases-overestimated-ice-core-study-suggests.html>

- The global climate is naturally variable. Anthropogenic CO₂ emissions add to that variability by changing the total radiative balance in the atmosphere.
- The IPCC has downplayed the role of the sun in climate change but there are Total Solar Irradiance reconstructions that imply it might have been important, and the modern record is uncertain due to an interruption in satellite coverage.
- Projections of anthropogenic emissions are combined with carbon cycle model estimates of atmospheric CO₂ removal to estimate future CO₂ concentrations and hence the radiative forcings. These are input to climate models to estimate future anthropogenic changes in the climate.
- IPCC emission scenarios envelopes have tended to exceed observed trends.
- The vast majority of academic climate “impacts” studies in recent years are based upon the extreme RCP8.5 scenario that is considered implausible; its usage as a business-as-usual scenario is misleading.
- Despite ample evidence that scenario envelopes are exaggerated, and despite criticism of this practice in the peer-reviewed literature, the IPCC’s most recent scenario set (SSP) perpetuates this malpractice.
- The global carbon cycle heavily dampens the effect of changes in local (e.g. U.S.) CO₂ emissions. Even global-scale emission reductions will have only small, much delayed effects.
- Knowing the magnitude of CO₂ warming requires knowing the strength of aerosol cooling. While that is uncertain, a substantial body of recent evidence points to it being relatively weak, implying CO₂ warming is likewise weak.

Scaffeta, Nicola, Richard C. Willson, Jae N. Lee and Dong Wu (2019) Modeling Quiet Solar Luminosity Variability from TSI Satellite Measurements and Proxy Models during 1980–2018. *Remote Sensing* 11(21) 2569 <https://doi.org/10.3390/rs11212569>

Connolly, Roman, Willie Soon, Michael Connolly et al. (2021) How much has the Sun influenced Northern Hemisphere temperature trends? An ongoing debate *Research in Astronomy and Astrophysics* 21(6) doi: 10.1088/1674-4527/21/6/131 <https://iopscience.iop.org/article/10.1088/1674-4527/21/6/131>

Zacharias, Pia (2014) An Independent Review of Existing Total Solar Irradiance Records. *Surveys in Geophysics* 35 pp. 897—912 <https://link.springer.com/article/10.1007/s10712-014-9294-y>

Liu, Pengfei et al. (2021) “Improved estimates of preindustrial biomass burning reduce the magnitude of aerosol climate forcing in the Southern Hemisphere” *Science Advances* 7(22) May 2021 <https://doi.org/10.1126/sciadv.abc1379>

Wang, C., Soden, B. J., Yang, W., & Vecchi, G. A. (2021). Compensation between cloud feedback and aerosol-cloud interaction in CMIP6 models. *Geophysical Research Letters*, 48, e2020GL091024. <https://doi.org/10.1029/2020GL091024>

5 Measuring Climate Sensitivity to CO₂ Forcing

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5.1 Introduction5.1 Model-based methods of computing climate sensitivity to GHGs

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The magnitude of the sensitivity of Earth's climate to increasing concentrations of CO₂ is at the heart of the scientific debate on anthropogenic climate change, and also the public debate on the appropriate policy response to increasing CO₂ in the atmosphere. Equilibrium Climate Sensitivity (ECS) refers to the expected amount of warming averaged over the Earth's surface in response to a doubling of CO₂, after all climate systems have had time to adjust. Some systems, like temperatures in the troposphere, adjust very rapidly. Others may take decades or even centuries, such as the deep ocean and the cryosphere. A related metric which is sometimes more helpful for analysis on shorter time scales is the Transient Climate Response (TCR) defined as the amount of warming after 70 years in which atmospheric CO₂ goes up by one percent annually.

In 1979 the Charney (1979) Report for the US National Academy of Sciences proposed that the most likely value for ECS was 3.0°C plus or minus 1.5°C. With only minor variations this range was adopted and reaffirmed by the IPCC until the most recent AR6. The ECS range between 1.5 and 4.5°C is characterized by the IPCC AR5 as the *likely* range (66 percent probability); the AR5 stated that ECS is *extremely unlikely* (95 percent probability) to be below 1.0°C and very unlikely (90 percent probability) to exceed 6.5°C. This range of ECS values has remained stubbornly wide, despite many individual studies claiming to narrow it. Most recently, the IPCC AR6 narrowed its assessment of the *likely* range of ECS to 2.5–4.0°C and the *very likely* range to be between 2.0 and 5.0°C. This narrowing of the range on the low end is disputed, as will be discussed below.

Although ECS is of intrinsic scientific interest it is also of central importance to evaluating the public danger posed by GHG emissions. Uncertainties about ECS are highly consequential for policy making. As will be discussed in Section Chapter 13, economic models take the ECS value from climate science and use it to project the costs of CO₂ emissions. The traditional ECS value (3.0 °C) has typically yielded modest global social costs of CO₂ emissions, enough to justify some policy actions though mostly deferred to later in the century. If ECS is very high (4.5°C or above) aggressive immediate emission controls become more imperative, whereas values closer to 2.0°C have been shown to be compatible with social costs of emissions being zero or even negative over the coming decades, imply that no CO₂ emission controls are economically justifiable (Dayaratna et al. 2016, 2020). Obtaining a precise ECS estimate is therefore important for policy guidance. Obtaining a precise estimate is impossible, policy making needs to account for the uncertainty.

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In large-scale General Circulation Models (GCMs, aka climate models) ECS is not imposed as a direct parameter, instead it emerges from the behaviour of the underlying components of the model. These, however, are under the control of the modeler, so ultimately a model's ECS can be said to be built into it. Direct warming from CO₂ doubling is only about 1°C (Hall and Manabe 1992); the rest, to the extent more happens, arises due to climate feedbacks which are inherently more difficult to predict and model.

In 1979 the Charney (1979) Report for the US National Academy of Sciences proposed that the most likely value for ECS was 3.0°C plus or minus 1.5°C. Hence the best estimate was a likely tripling of the CO₂ effect through feedbacks. With only minor variations this range was adopted and reaffirmed by the IPCC until the most recent AR6.

5.1.2 Model-based methods of computing climate sensitivity to GHGs

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The ECS range has been obtained primarily by examining the behaviour of climate models, but since key components of models are under the control of modelers this is not dispositive of the actual climate's sensitivity.

There are approximately three dozen computer climate models operated by research groups around the world (Cannon 2024). GCMs are valuable tools for understanding the climate system from a theoretical perspective. But the models have become so complex, often with 1 million or more lines of computer code (Brown-Steiner 2024), that it would be prohibitively expensive and time consuming for anyone to replicate the models' projections of climate change, let alone test the myriad model approximations embedded in the computer codes; a climate model typically takes hundreds of experts many years to develop (McSweeney and Hausfather 2018). As a result, these models are published in the scientific literature with little to no independent evaluation (Pirtle et al 2010). Climate modeling thus stands as an unusual class of scientific endeavor wherein researchers validating the scientific claims of others — a hallmark of science (National Academy of Science 2019) — becomes impractical, if not impossible.

In large-scale General Circulation Models (GCMs, aka climate models) ECS is not imposed as a direct parameter. Instead it emerges from the behaviour of the underlying components of the model. Collections of parameterizations are often chosen to produce an expected value of climate sensitivity, particularly with regards to sub-grid-scale cloud processes. Otherwise plausible models and parameter selections have been discarded because of perceived conflict with this warming rate, or aversion to a model's climate sensitivity being outside an accepted range. For example, Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute climate model:

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"We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming: an endeavor which has clearly been successful. Due to the historical order of events, the choice was to do this practically by targeting an ECS of about 3 K using cloud feedbacks, [emphasis added] as opposed to tuning the aerosol forcing."

In other words, the modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

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Direct warming from CO₂ doubling is only about 1°C (Hall and Manabe 1997); the rest to the extent ~~more happens, arises due to~~ higher values arise ~~to~~ from climate feedbacks that are not explicitly resolved by the model but rely on parameterizations of physical processes which are inherently more difficult to predict and model. Higher values of ECS arise primarily from positive cloud feedbacks. The magnitude, and even the sign, of cloud feedbacks is the greatest source of uncertainty. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle [source 35]. It is difficult for climate models to simulate any of these cloud processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks [source 36].

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ECS can be determined from climate model simulations by doubling the concentration of CO₂, allowing several centuries for the warming to equilibrate. To avoid the necessity of long simulations, "effective climate sensitivity" is commonly evaluated from a 150-year simulation in response to a

sudden quadrupling of CO₂. The spread of ECS values from the CMIP5 climate models (used in the AR5) was 2.0–4.7°C; the spread has increased for the CMIP6 models (used in the AR6) to between 1.8 and 5.7°C [sources 37,38]. Far from the science being settled in relation to the response of the climate system to increasing greenhouse gas concentrations, insofar as it is represented by climate models, uncertainties appear to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models [source 39].

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~~THIS ISN'T VERY RELEVANT.~~ There are approximately three dozen computer climate models operated by research groups around the world (Cannon 2024). GCMs are valuable tools for understanding the climate system from a theoretical perspective. But the models have become so complex, often with 1 million or more lines of computer code (Brown-Steiner 2024), that it would be prohibitively expensive and time-consuming for anyone to replicate the models' projections of climate change, let alone test the myriad model approximations embedded in the computer code: a climate model typically takes hundreds of experts many years to develop (McSweeney and Hausfather 2010). As a result, these models are published in the scientific literature with little to no independent evaluation (Pirille et al. 2010). Climate modeling thus stands as an unusual class of scientific endeavor wherein researchers validating the scientific claims of others—a hallmark of science (National Academy of Science 2019)—becomes impractical, if not impossible.

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While the models are often touted as being accurate representations of the "basic physics" governing the climate system, they still have problems with model "drift," in which the models slowly change temperature over centuries for no apparent reason (Grandey et al. 2023). The tendency to drift is adjusted for by climate modelers imposing the arbitrary assumption that Earth's climate system does not produce long-term climate change, unless caused by humans (Sen Gupta et al. 2013). By suppressing all slow-moving warming and cooling in this way this biases model-based research away from potential natural causes of climate change, since it implies there can be no warming trends except in response to external forcing. In addition recent research suggests many models do not even conserve energy (Irving 2021)—a violation of the First Law of Thermodynamics. The First Law holds that energy can be neither created nor destroyed; to the extent that climate models fail to conserve energy, it can spontaneously appear (or disappear) for no apparent reason, causing a fictitious temperature change. This is a particularly important consideration since global warming theory is first and foremost based upon tiny changes in the global energy balance assuming the First Law holds.

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Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6 (2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying on other methods in its assessment instead, chiefly a recent empirical estimate.

For all these reasons it should come as no surprise that the various models' responses to a hypothetical doubling of atmospheric CO₂ above pre-industrial levels produces a very wide range of ECS values in current models, from 1.83°C to 5.64°C in the IPCC AR6. This wide range of responses—the largest in over 30 years of the global climate modeling enterprise—demonstrates large remaining uncertainties in climate modeling and thus in the projection of global climate impacts imputed to human activities. It also implies that ECS cannot be determined from climate models alone since the range is too wide to be informative. For that reason scientists have increasingly turned to empirical methods.

4.5.2.3 Empirical Data-driven methods of computing climate sensitivity to GHGs

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Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes, aerosols) have changed in the past [source 40]. Using this information, a simple empirical model called an Energy Balance Model can be estimated. It requires estimating a feedback parameter which appears in the denominator of the resulting equation for ECS. ~~NO EQUATIONS~~ whose uncertainties are highly amplified in the resulting ECS (Roe and Baker, 2007). A small amount of uncertainty about the number in the denominator of a fraction can lead to very large uncertainties in the magnitude of the fraction itself. Roe and Baker (2007) pointed out that for this reason uncertainties in climate feedbacks are "highly amplified" in the resulting ECS.

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The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and the ocean data is inadequate. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects need to be estimated to isolate the warming effect of CO₂. Over time, the IPCC's estimate of the cooling effect of aerosols has declined (Lewis 2022).

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Paleoclimate proxies are also used to evaluate the sensitivity of past climates by comparing paleoclimate changes in the Earth's temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today [source 41]. The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states may not be representative of the current state of the climate system.

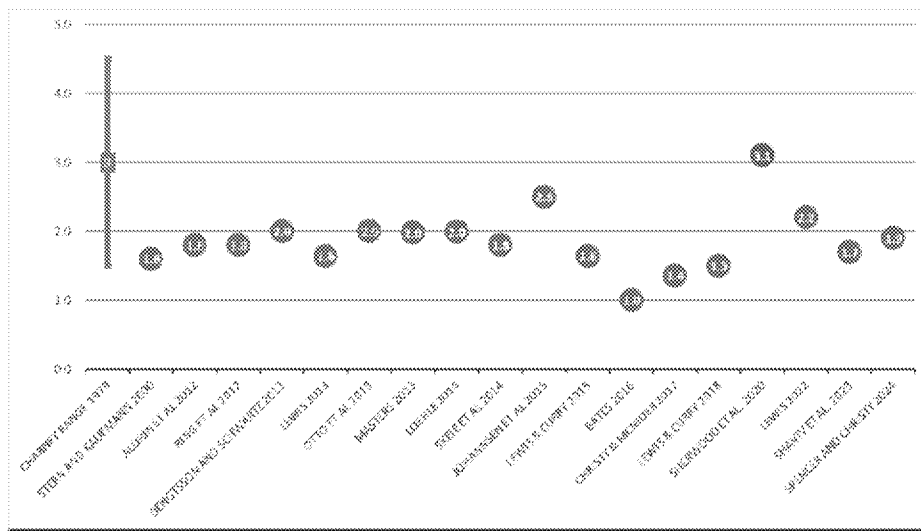
A significant amount of effort since the EF has gone into estimating ECS empirically. There are several challenges to this work:

- First, it requires good data but observations of some key climatic systems, especially the oceans, are available in only very limited amounts.
- Second, identifying the effect of CO₂ requires simultaneously identifying the effect of aerosols. Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects need to be estimated to isolate the warming effect of CO₂. Over time, the IPCC's estimate of the cooling effect of aerosols has declined (Lewis 2022).
- Third, the simple empirical model typically used for the estimation, called an Energy Balance Model, requires estimating a feedback parameter which appears in the denominator of the equation for ECS. A small amount of uncertainty about the number in the denominator of a fraction can lead to very large uncertainties in the magnitude of the fraction itself. Roe and Baker (2007) pointed out that uncertainties in climate feedbacks are "highly amplified" in the resulting ECS.

Since 2012 many studies have appeared in the literature tackling these various uncertainties. A recurring theme in the climate literature is that ECS estimates based on historical data turn out to be smaller than ECS estimates inferred from encoded in climate models (Sherwood and Forest 2024). An early empirical estimate (Stern and Kaufmann 2000) was 1.6°C, though this predated development of the Energy Balance Model method. Figure 4.25.1 shows the point or best estimates from 17 subsequent studies all appearing in the peer-reviewed literature after the TSD since 2012. The Charney range is shown for contrast. The average ECS point estimate in the post-2012 sample is 1.8°C. The highest estimate, from Sherwood et al. (2020), is shown in red: it is the one that was used highlighted by the IPCC for the AR6 and used to guide their assessment of the ECS range (Forster et al. 2021). The one adjacent to it, Lewis (2022), was published subsequent to the AR6 and presented an extensive critique of Sherwood et al. (2020).

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shows the result of, among other things, using the same statistical method (Bayesian inference) but applying more updated aerosol forcing data in the AR6 as well as some other recent updates to the source data. These updates dropped the ECS best estimate to 2.2°C closer to the usual empirical range. The IPCC, following Sherwood et al. (2020) had estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis (2022) estimated it was over 50 percent.



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Figure 4.25.1: Empirical best estimates of ECS. Vertical axis: °C.

(Judy I reinserted this figure as I think it is an important visual indicator that Lewis 2022 is not a one-off outlier.)

I don't think this is needed. Lewis (2022) is not a historical empirical method, but rather uses the same approach as Sherwood et al. and AR6 in combining historical, paleo and feedback approaches. I don't think that the older ones are useful because the data is pretty old, and methods outdated. Lewis (2022) is clearly within the the AR5 range, I don't think we need to resurrect the old stuff.

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Key concerns raised by Lewis include methodological errors, outdated input values, and use of subjective versus objective Bayesian priors in the analysis. Lewis' analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood et al. analysis – median 2.16°C (1.75–2.7°C in the 17–83 percent likely range), and 1.55–3.2°C in the 5–95 percent very likely range. Lewis' analysis implies that climate sensitivity is considerably more likely to be below 2°C than above 2.5°C. The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis (2022) estimated it to be over 50 percent. The most recent publications on the debate between Sherwood et al. and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

A recent hypothesis argument, which the IPCC AR6 emphasized, is that empirical data-driven ECS estimates might understate the future warming response to GHGs due to based on a so-called “pattern effect” (Forster et al 2021). The tropical Pacific is believed to be highly influential on the overall efficiency with which the Earth's climate radiates heat to space, but heat in some parts regions heat is more efficiently removed from the climate system than from others. If in a warming climate there is a weakening of the west-to-east temperature gradient in the tropical Pacific the result would be a concentration of warming in a region where heat is less efficiently removed, raising the ECS of the Earth's climate system. Most climate models simulate that rising GHGs will weaken the east-west temperature gradient, which led the IPCC in the AR6 to conclude that empirical data-driven ECS estimates understated what would be the future observed ECS value.

However, Seager et al. (2019) pointed out that, contrary to models, the east-west temperature gradient has been strengthening rather than weakening over time. They further argued that the mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic dynamics and there is no reason to expect the gradient to weaken. A similar argument was recently made by Lee et al. (2024), who concluded that “the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere⁴⁷,” in other words GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate may be lower than at present current estimates.

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5.5 Transient Climate Response

The Transient Climate Response (TCR) is of greater utility in providing an observational constraint on climate sensitivity. TCR is the amount of warming that would occur at the time when CO₂ doubles, having increased gradually by 1 percent each year over a period of 70 years. Relative to the ECS, observationally-determined values of TCR avoid the problems of uncertainties in ocean heat uptake and the fuzzy boundary in defining equilibrium arising from a range of timescales for the longer-term feedback processes (e.g., ice sheets). TCR is more generally related to peak warming and better constrained by historical warming than ECS. The IPCC AR6 judged the very likely range of TCR to be 1.2–2.4°C [source 47]. In contrast to ECS, the upper bound of the TCR is more tightly constrained. For comparison, the TCR values determined by Lewis (2023) is 1.25 to 2.0°C, showing much better agreement with the AR6 values than was seen in a comparison of the ECS values.

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A related but more flexible parameter is the Transient Response to cumulative carbon Emissions, or TCRE, which relates global temperature change to the cumulative emissions. TCRE is based upon a linear relationship between global average temperature and cumulative emissions, which holds for cumulative emissions of up to 2 teratons of carbon. For a given value of TCRE, we can calculate the estimated amount of warming expected over a future period in response to scenarios of cumulative carbon emission. The IPCC AR6 provides a very likely range for TCRE of 1.0–2.3°C, with a median value of 1.6°C.48

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As will be discussed in ~~Section~~ Chapter 65 a real-world ECS below the model average is supported by studies which show climate models on average estimate too much warming at the surface and in the troposphere compared to observations over the past 50 years. Also it aligns with evidence from consistent fingerprinting (Section 67) that model responses to GHGs need to be scaled down quite a bit to align with observed trends.

5.6 Summary

In the past 5 years, there is a growing realization that climate models are not fit for the purpose of determining the sensitivity of the climate to increasing CO₂ (ECS), owing to the dependence of this sensitivity on poorly resolved processes related to clouds and water vapor.

Data-driven approaches using historical data and paleoclimate reconstructions are now regarded as more reliable for determining ECS, but their reliability is diminished by data inadequacies. The IPCC AR6 upper bound for the *likely* range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by the paleoclimatic estimates of the ECS. The IPCC AR6 lower bound for the *likely* range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound of the likely range of ECS has received a substantial challenge from the analysis of Lewis (2022, 2025) that finds the lower bound of the likely range to be 1.75°C with a median value of 2.16°C. Other lines of evidence supporting a lower bound on the ECS range below the IPCC AR6 value are discussed in Chapters 6 and 7.

Estimates of the transient climate response (TCR, TCRE) are more tightly constrained on the upper bound than the ECS.

[Andy I took out the assessed value statement since I don't think we need to generate one and I wouldn't know how to do it] **AGREED**

Mauritsen, T., & Roeckner, E. (2020). Tuning the MPI-ESM1.2 global climate model to improve the match with instrumental record warming by lowering its climate sensitivity. *Journal of Advances in Modeling Earth Systems*, 12, e2019MS002037. [HYPERLINK "https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2019MS002037"]

Zelinka, M. D., Myers, T. A., McCoy, D. T., Po-Chedley, S., Caldwell, P. M., Cepni, P., et al. (2020). Causes of higher climate sensitivity in CMIP6 models. *Geophysical Research Letters*, 47, e2019GL085782. [HYPERLINK "https://doi.org/10.1029/2019GL085782"]

In summary:

- ECS cannot be determined from climate modeling alone since models are too complex and uncertain to narrow the range
- Climate models on average embed process assumptions that yield a projected warming of about 3.0°C from CO₂. Empirical estimates since the TSD however imply the climate is much less sensitive to CO₂ than this.
- A large number of empirical ECS estimates have been centered at or below 2°C. This aligns with other independent forms of empirical evidence pointing towards low ECS.

8 Extreme weather in the US and elsewhere

8.1 Introduction

Weather extremes, usually related to temperature and/or precipitation, often disrupt infrastructure and therefore human health and thriveability. Indeed, the ability of any surface-dwelling species to live productively is somewhat constrained by these extremes which in essence create the bounding limits for survival. The issue here is whether these extremes, and their attendant potential danger, may be changing and if so whether the change is in response to increases in infrared-absorbing greenhouse gases (GHGs) (e.g., IPCC AR6 Seneviratne et al. 2021).

Unfortunately, the sample of time from which we are able to quantitatively analyze variations in extreme events is quite brief, around 130 years. This period certainly does not begin to contain all of the extreme events that the climate system is able to create naturally. Over geologic time the climate system has generated an (essentially) infinite variety of patterns and extremes which humans have never observed, and thus do not enter our databases from which extreme statistics are determined [see *Perils of short data records* below]. Thus, assuming that a climate pattern or event hitherto not experienced in our lifetime must therefore be the result of enhanced GHG concentrations requires the assumption that natural variations are insignificant.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of *Long Term Persistence* (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2015). LTP has a formal mathematical definition but it can be thought of intuitively as the presence of natural variations with strong autocorrelation properties that result in cycle-like behavior on long time scales. The presence of LTP requires very long data samples to obtain accurate estimates of variance; analysis of data samples that are short relative to the LTP scale will tend to yield underestimated variances which in turn yields overstated significance of apparent trends and underestimation of the likelihood of extreme events (Cohn and Lins 2005).

With this caveat in mind we examine the evidence for changes in weather and climate extremes. It has become routine in media discussions, government and private sector discussions and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and climate change. Yet expert assessments have not typically drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing. In the Appendix to this chapter we provide excerpts of these findings from previous IPCC and NCA assessments.

8.2 Global and continental indicators of extreme weather trends

8.2.1 Tropical Cyclones (TCs)

Hurricane strength records for the North Atlantic and the Western Pacific go back to 1950 and the record does not show an increase in either total or major TCs. Figure 8.1 was published by Roger Pielke Jr. as an update to the Best Track data series originally presented in Weinkle et al. (2012).

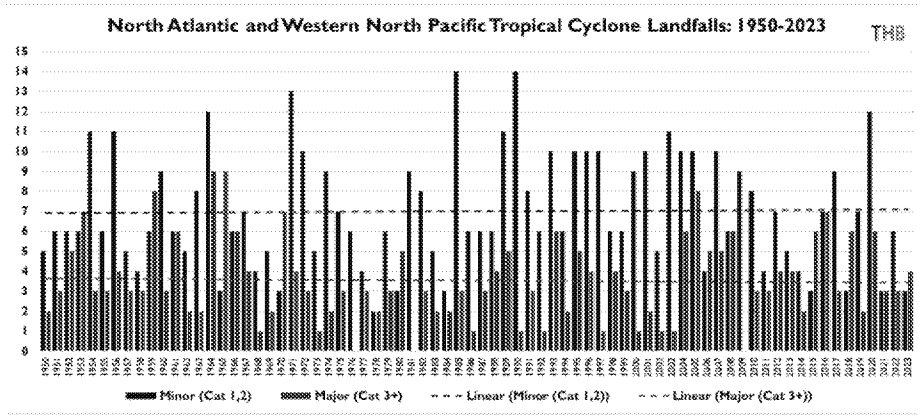


Figure 8.1. Tropical Cyclone Landfalls. Source: [[HYPERLINK "https://rogerpielkejr.substack.com/p/global-tropical-cyclones"](https://rogerpielkejr.substack.com/p/global-tropical-cyclones)], Weinkle et al. (2012)

After 1980, as shown in Figure 8.2, which reproduces data from the Climate Atlas of Dr. Ryan Maue neither the total number of hurricanes nor the frequency of major ones have become more common since 1980, indeed both have trended down since the 1990s:

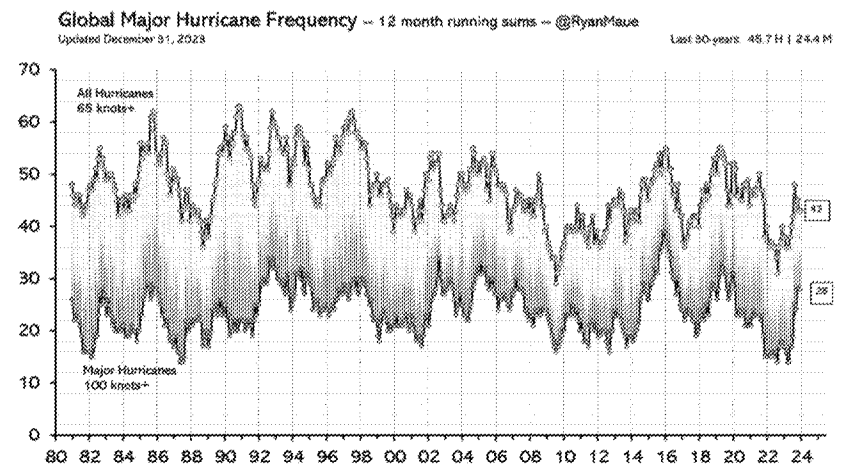


Figure 8.2: Global hurricane frequency. Source: Maue (2024)

A metric that combines the number and frequency of TCs is the Accumulated Cyclone Energy or ACE Index maintained at Colorado State University, shown in Figure 8.3.

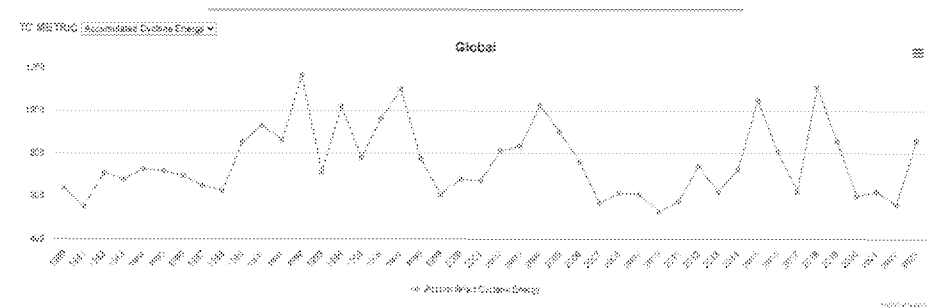


Figure 8.3: Global Accumulated Cyclone Energy. Source: Klotzbach (2025)
 [HYPERLINK "<https://tropical.atmos.colostate.edu/Realtime/index.php?arch&loc=global>"]

As is clear, it is also not increasing and since 1990 has declined slightly.

Climate models project declining hurricane formation rates in a warming climate (Chand et al. 2022). Climate models also project fewer Tropical Cyclones under future global warming, and even though models project they will increase in strength, the annual averages of rainfall maxima decline (Stansfield et al. 2020). Note that Tu et al. (2024) report that the Power Dissipation Index (PDI), a measure of the destructiveness of hurricanes, has either remained unchanged or has declined in all global oceanic basins since the mid-1990s.

8.2.2 Wildfires

As shown in Figures 8.4 and 8.5 global wildfire activity as measured by European Space Agency peaked over a decade ago and shows a downward trend since.

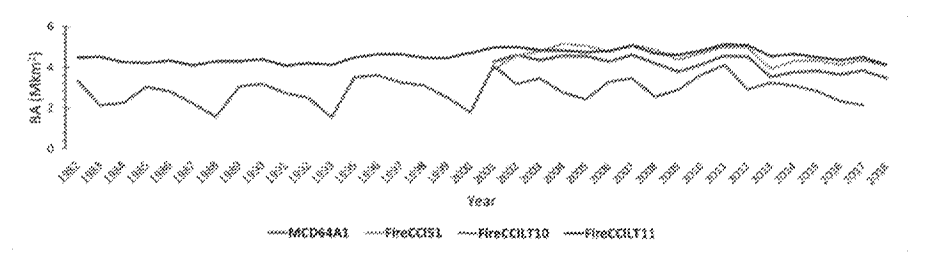


Figure 8.4: Global wildfire 1982-2018. Source: Copied from Oton et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used.

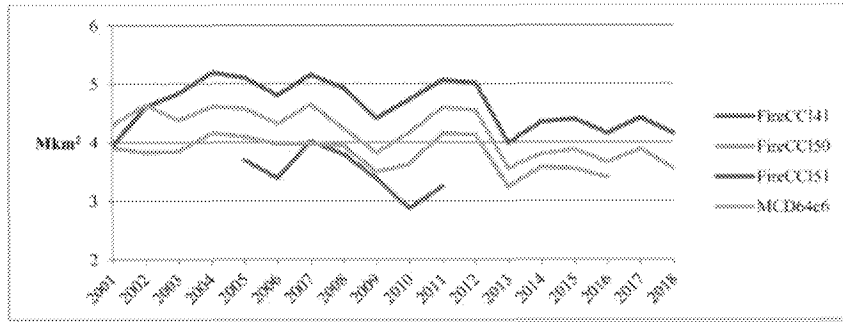


Figure 8.5: Global wildfire 2001-2018. Source: Copied from Lizundia-Loiola et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used

US data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 8.6.

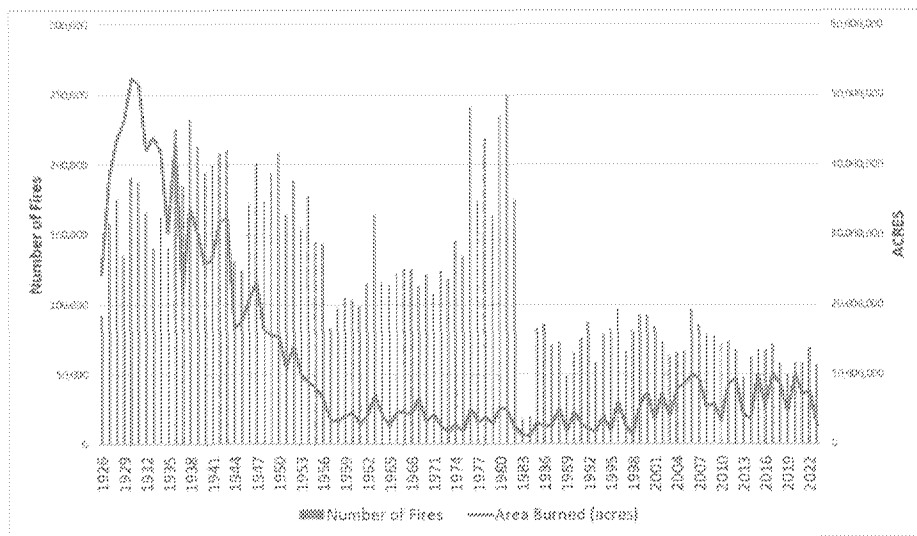


Figure 8.6: US wildfires 1926 to 2023. Source: National InterAgency Fire Centre data Pre-2017 (archived)

[[HYPERLINK "file:///C:/Users/Porter%20Hill/Dropbox/Brucehaven/Projects/DoE/Ross%20drafts/Pre-2017:/web.archive.org/web/20200212033452/https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html"](https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html)]. 2018-2023: [[HYPERLINK "https://www.nifc.gov/fire-information/statistics/wildfires"](https://www.nifc.gov/fire-information/statistics/wildfires)]

Note the NIFC has removed the pre-1960 data from its current website. They claim it is because measurement methods changed after 1960. This explanation seems inadequate since agencies blend temperature and extreme weather data series in other context when measurement systems changed. In this case if anything the measurement of wildfires has improved since the early 20th century so any bias will be towards understating early wildfire counts. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

It is difficult to establish a natural baseline for wildfire activity because of active fire suppression activity since 1900. Paleoclimatic evidence indicates, however, that past wildfire activity was much higher than at present. Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US for the past 1400 years. They also fit a model to predict expected fire activity as a function of climatic conditions. The results are summarized in Figure 8.7 below (from Figure 2 in their paper).

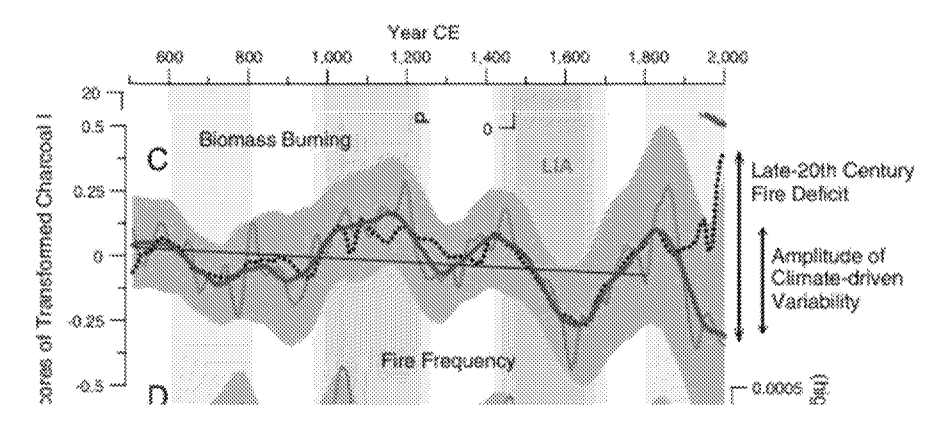


Figure 8.7: Fire frequency and fire deficit in the US. Source: Copied from Marlon et al. (2012)

In their figure the red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on the statistical model. The gap at the end implies there has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century it was less than what would have been observed in previous centuries based on the climatic conditions. Parks et al. (2025) likewise find that despite the recent increase in wildfire burn area in North America, relative to historical wildfire regimes there remains a significant wildfire deficit.

8.2.3 Precipitation

Figure 8.8 shows that US long term data from NOAA shows an insignificantly increasing tendency toward extreme wetness (+0.001% per year)

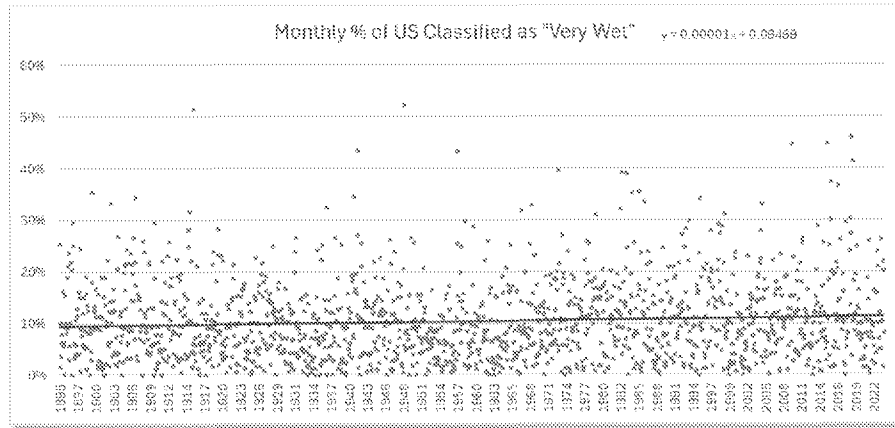


Figure 8.8: Long term US wetness (%). Source: NOAA [[HYPERLINK "https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0"](https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0)]

Precipitation will be discussed further in the review of CONUS data below.

8.2.4 Drought

As shown in Figure 8.9 US long term data (NOAA) shows an insignificantly declining tendency toward extreme dryness (-0.001% per year)

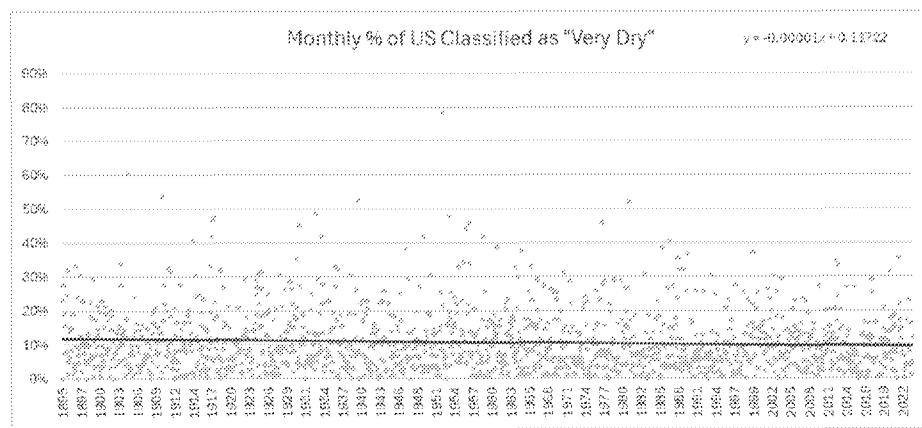


Figure 8.9: US dryness (%) 1895—2023. Source: NOAA [[HYPERLINK "https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0"](https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0)]

Kogan et al. (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: “it is possible to state firmly that global and main grain countries’ drought area and intensity trends have not been following global climate warmings since 1980’s.”

8.3 Analysis of Conterminous US (CONUS) data on temperature and precipitation extremes

8.3.1 CONUS daily temperatures are becoming less extreme

Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although errors certainly reside in the dataset, with over 1,000 stations any underlying signal we discover can be characterized by relatively high confidence.

We begin with the question of whether the occurrence of daily record high or low temperatures changed has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time the expected number of records for TMax would be 1.21 per year and for TMin 0.96 per year. Figure 8.10 indicates the observed distribution in time of the occurrence of these extreme events.

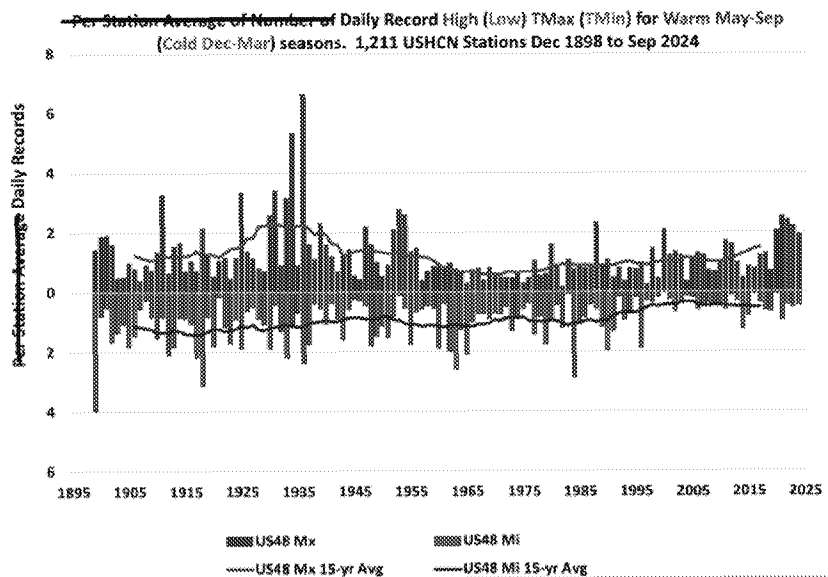


Figure 8.10 Number of daily record High (red) and Low (blue) for warm and cold seasons in the CONUS. The lines represent 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

The results indicate a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s peaking in 1936. On a per-station average, 60% of the TMax records and 59% of the TMin records occurred in the first half of the period (1899-1961).

On the cold side, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 2nd. The frequency of cold records has declined, especially over the last quarter of the period in which only 13% of the extreme cold events were measured. In contrast, 25% of the extreme TMax records were achieved in the last quarter in accordance with statistical expectations. These general features have been noted in past assessments (IPCC AR5, IPCC AR6, NCA4, NCA5). Combining the two records the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 8.11. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated and converted to anomalies relative to the station's long term warm and cold season (respectively) averages. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 8.11 shows the 15-year trailing average of this measure which has clearly declined over the past century.

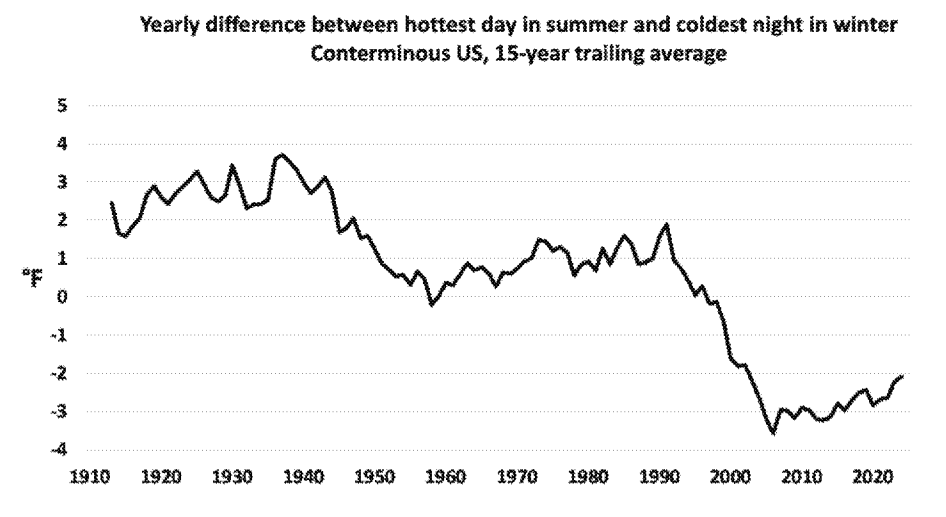


Figure 8.11. 15-year trailing average of the difference each year of each station's hottest warm-season TMax and coldest cold-season TMin relative to the long-term average.

The average difference for each station between the hottest summer TMax and coldest winter TMin has declined about 5°F in the past 126 years. The decline is due mostly to warming winter TMin, but a decline in the magnitude of summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (Spencer et al. 2025).

Summarizing Figures 8.10 and 8.11, while temperature extremes are regularly experienced in the US and attract a great deal of media attention, long term records show the US climate has become less extreme over time when measured in terms of the range between warm season maxima and cold season minima.

8.3.2 Exceedances of a heat threshold

Under the heading of "The Risk of Temperature Extremes is Changing", the most recent US National Climate Assessment report (NCA5) notes the increase in a threshold metric of number of days at or above 95°F, stating,

"The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021."

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations which have near 95°F TMax average

temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not impact the results much at all. In the past 126 years, the average CONUS station experienced 129 days exceeding 95°F per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, one needs to view such threshold analyses with caution.

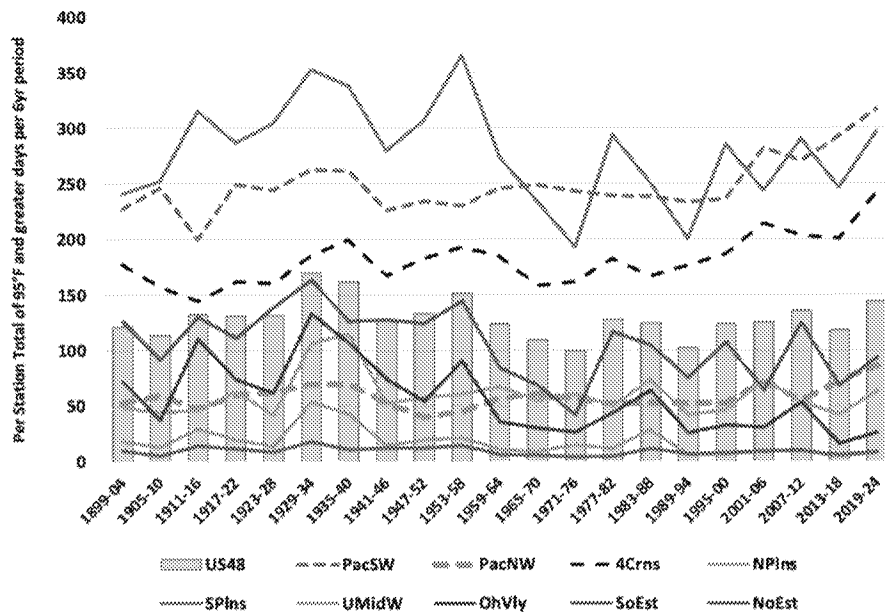


Figure 8.12. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, US 48 (bars) and regions (lines).

In Fig. 8.12 we see that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 is referenced as supportive information for the NCA5 claim, an event examined more closely in section 6.4. The evidence indicates it was a “black swan” event, i.e. a single, unprecedented event in the existing record suggesting it is not indicative of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW was +10.8 C, the most extreme NH grid point summer anomaly in the 46 years from over 4 million grids. In contrast, the global anomaly was virtually zero (+0.03 C, Mass et al. 2024).

The heading “The Risk of Temperature Extremes is Changing” suggests positive trends are now being observed in threshold temperatures on a widespread basis, but that is not evidenced in the combined CONUS results of the figures above.

8.3.3 Heatwaves

Of more impact than a single daily record is the phenomena of heatwaves, or consecutive days which exceed an extreme threshold. For this study, the metric will be the number of “Heatwave Days” defined as the sum of all days in May-Sep each year which exceed the 90th percentile that occur within consecutive periods of at least six days in length. This is equivalent to the method in NCA5 except the reference period here is the entire record 1899-2024 while NCA5 limited the reference period to 1961-1990, a cool episode. By selecting 1961-1990, the occurrence of positive results (days exceeding the 90th percentile) will be enhanced in periods warmer than the reference base, especially if starting in 1960 and moving to the present (see *Urban Influences* below).

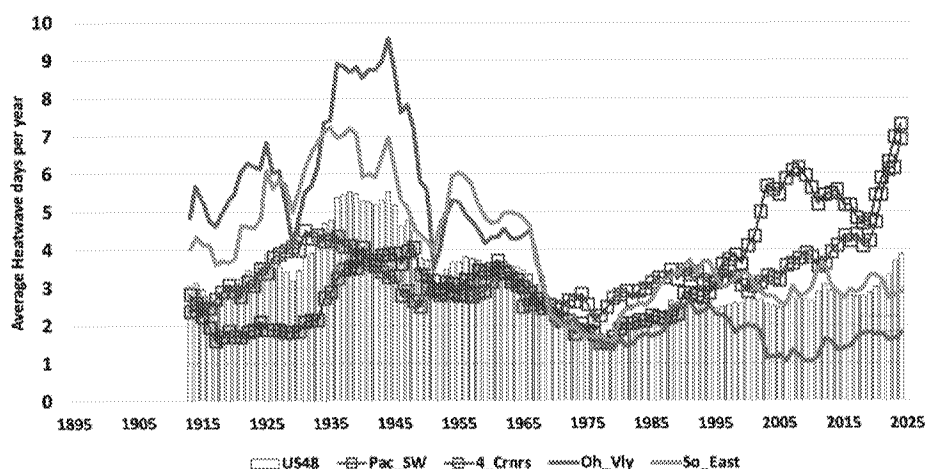


Figure 8.13 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (purple squares, CA, NV), 4_Crnrs (red squares, AZ, NM, UT, CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure 8.13 indicates again the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, as seen in the regional values for the Ohio Valley and the Southeast as examples. The West has seen a recent increase of heatwave days and the two regions with the highest number are shown, the Pacific Southwest and the Four-Corners (NCA5). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West.

Of interest here is the regional variation of this metric. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per 15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains,

Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

Urban influences

The NCA5 directs readers to the website [[HYPERLINK "https://www.globalchange.gov/indicators/heat-waves"](https://www.globalchange.gov/indicators/heat-waves)] (USGCRP 2023) to view the number of urban heatwaves by decade from the 1960s. The figure reveals a monotonic increase in each decade from 2 occurrences per year in the 1960s to 6 in the 2020s. The definition of a heatwave is unusual but practical from a human discomfort perspective - a period of at least 2 consecutive days when the apparent minimum temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest cities in the US.

These increasing values since 1960 presented in USGCRP (2023) are entirely reasonable, but for at least two reasons unrelated to GHG emissions. Urbanization in these cities is a major factor in the rise of TMin relative to co-located TMax and relative to TMin at rural stations. Also, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. This does not dismiss the real rise in nighttime temperatures in major US cities and the societal impacts associated with these changes. However, we note for a variety of reasons, that summer TMax (especially in rural areas) serves as better response variable for detecting potential changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves in the CONUS.

8.3.4 Extremes in daily precipitation.

Due to its stochastic and episodic character, precipitation requires careful statistical treatment to understand variability over long time periods (see *8.1 Introduction*). The US National Climate Assessments (NCA4, NCA5) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme events are in the Northeast and least in the West, which is counter to the changes in temperature extremes shown above.

McKittrick and Christy (2019) examined long-term and consistent station observations of daily precipitation to test some of these NCA claims for the Southeast and West Coast. In neither case when the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978) were the trends significant. For this report we update these findings with similarly constructed observations from 29 stations on the Pacific Coast (1893ff from San Diego CA to Blaine WA, see Figure 8.14), 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC, see Figure 8.15), and 21 stations in the Northeast (1888ff from Buffalo NY to Gardiner ME, see Figure 8.16).

In the Pacific region, over the whole sample, the trend in average precipitation is negative and significant in Astoria and insignificant elsewhere. The trend in rainfall variance is positive and significant in Big Sur and insignificant elsewhere. The trend in daily maximum precipitation is positive and significant in Aberdeen and Big Sur and negative and significant in Newport and

insignificant elsewhere. Averaged over all stations in the region none of these three trend parameters is statistically significant.

In the Southeast region over the whole sample the trend in average precipitation is positive and significant only in Mobile and Quitman, the trend in rainfall variance is positive and significant only in Mobile and the trend in daily maximum precipitation is positive and significant only in Vicksburg and Norfolk. Averaged over all stations in the region none of these three trend parameters is statistically significant.

The Northeast region exhibits a pattern of increasing average rainfall. The trend in average precipitation is positive and significant in 9 of 21 locations and in the region averaged overall. The trend in rainfall variance is positive and significant only in Portland, Albany and Buffalo and insignificant elsewhere and not in the regional average. The trend in daily maximum precipitation is positive and significant only in Portland ME and Gardiner ME and insignificant elsewhere and not in the regional average.

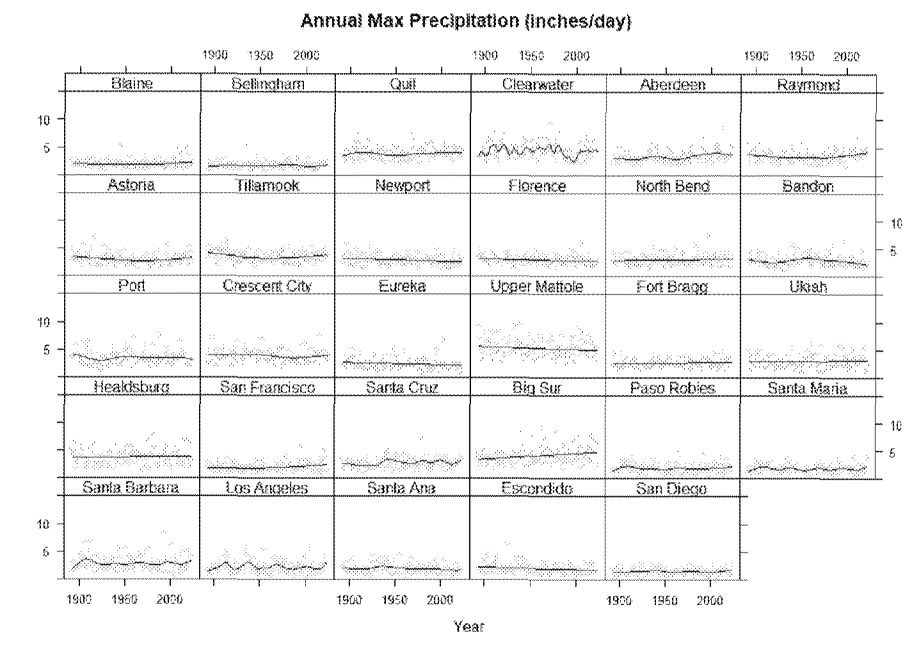


Figure 8.11 Annual maximum precipitation for 29 Pacific stations 1893 to present

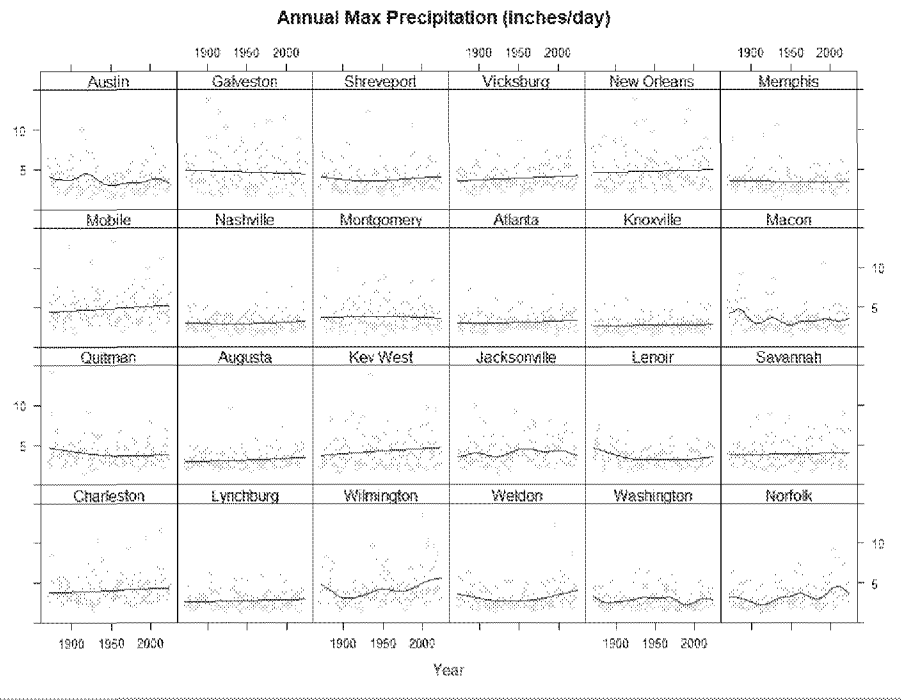


Figure 8.12 Annual maximum precipitation for 24 Southeast stations 1872 to present

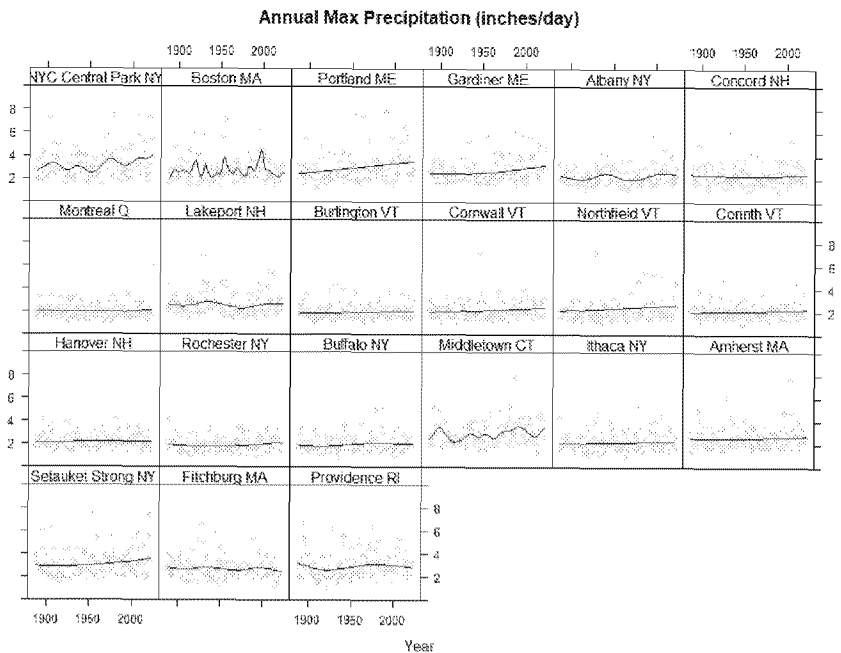


Figure 8.13 Annual maximum precipitation for 21 Northeast stations 1888 to present

Pacific Coast heavy rainfall events

The Pacific Coast receives considerable amounts of precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov et al. 2017, Pan et al. 2024). The worst-known such event in recent history was the ArkStorm that occurred between December 1861 and January 1862, which dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter et al. 2011).

SIDEBAR: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 8.1.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023
14-day	12.62	2023

30-day 18.93 1998
Table 8.1: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent data. 2023 appears to be an exceptional year and since it is near the end of the sample it would point to the possibility that the climate has shifted into a potentially more hazardous state.

But if we extend the record back to 1850 the picture changes. Table 8.2 shows that the record-setting events all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th. Also, comparing the records of the two charts the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 8.2: Extreme rainfall records, San Francisco, 1850-2024.

The characterization of the range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter et al. (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ArkStorm struck the region. Thus, such extreme events have impacted the region about every 300 years, though not since 1895.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (see 6.4). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50% determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur.

We examine occurrences of 5-day deluges as follows. In a 130-year span there are 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values. A single year may have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation then the total number of these events across all stations should be evenly spread out on an annual basis. In Fig. 8.14 we show the distribution in time of these events. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of these types of precipitation metrics, there is no indication of a tendency to become more frequent over time.

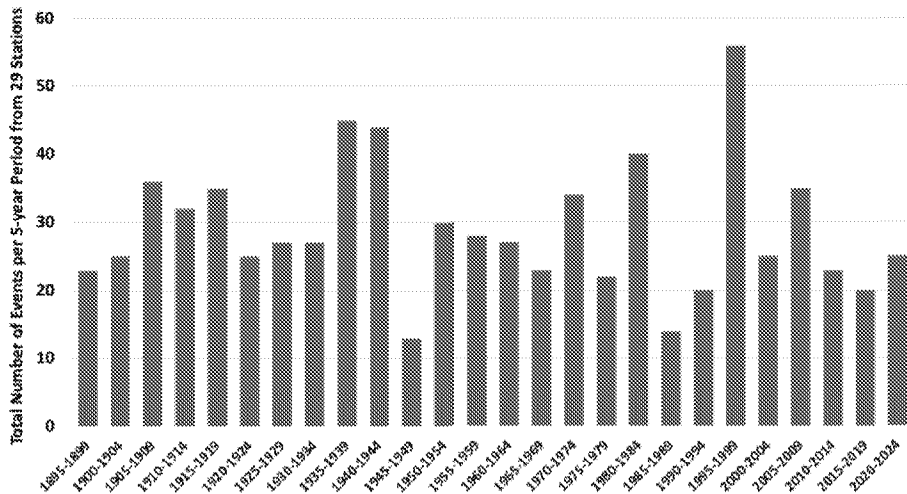


Figure 8.14. The time distribution by 5-year periods of the 26 heaviest occurrences for each station (i.e., nominal 1-in-5 year event).

Southeast heavy rainfall events

The temporal pattern of 5-day totals of the 1-in-5yr heavy events in the humid Southeast (Figure 8.15) is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 of a tendency for an increasing frequency of heavy events, due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

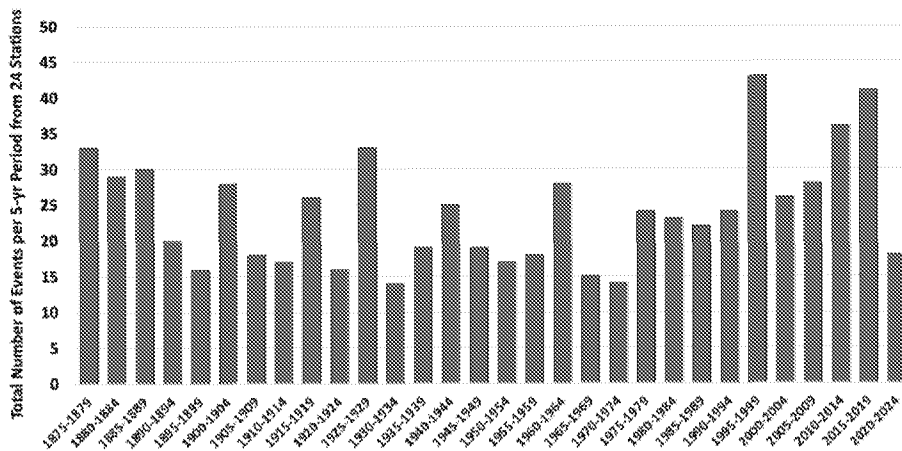


Figure 8.15. As above but for the 30 heaviest 1-in-5yr events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

Northwest heavy rainfall events

Fig. 8.16 shows the 27 (1-in-5yr) heaviest 3-day events for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest variations in time. In this region, 72% of the events occur during June to October and are dominated by tropical incursions of hurricanes, tropical storms or tropical storms that transition to extratropical systems. According to NCA4 and NCA5 this region experienced the largest increases in extreme events, so it shall be examined more closely.

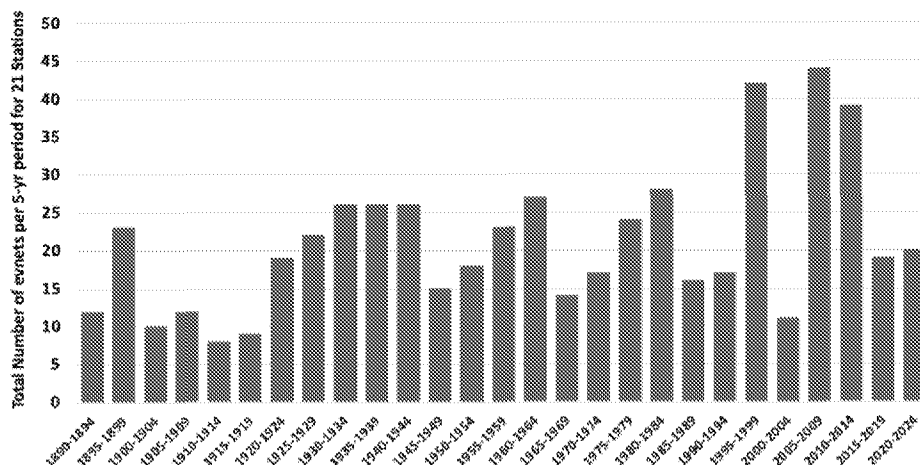


Figure 8.16. Time distribution of the heaviest 27 (1-in-5yr) heaviest 3-day precipitation events for 21 stations from NY to ME, including Montreal.

Howarth et al. (2019) report differences in the Northeast between two 18-year periods: 1979-96 and 1997-2014 (a similar region as in Fig. 8.16 that includes PA and NJ) of various precipitation extremes. One metric which indicated a dramatic increase (317%) was found for 24-hr events > 6 inches. This high increase is due to the very small numbers of such events of which there were only 6 in the first period and 25 in the second as reported for 58 stations. This high percentage increase is due to the very small numbers of the events; only 6 in the first period and 25 in the second. Most of the stations, did not record such an event suggesting these erratic, episodic events over brief, 18-yr periods, need scrutiny by additional statistical methods.

Using the information in Fig. 8.16 over the same years as Howarth et al. we find a 51% increase in the frequency of heavy events between the two periods. One can see in Fig. 8.16 that it was unfortunate that Howarth et al. ended in 2014 prior to a return to the long-term average of such events.

A feature of Howarth et al. is the use of single day totals which is questionable because extreme events are often spread across the time-of-observation boundary. Thus stations measuring at 0700 LT versus those at Midnight will have differing results for a particular event which would then have major impacts on counting these events. We use the 3-day totals in Fig. 8.16 to be sure to capture the extent of these extreme downpours. In any case, we can confirm that the period 1997 to 2014 experienced a cluster of heavier events as Howarth et al. have documented.

Howarth's most remarkable claim (317% increase in 6" days) is potentially misleading because it is a threshold statistic (see 8.3.2 above) and a ratio of small numbers over a short period. The result is not representative of *relative* extreme events for the whole region since the majority of stations never experienced a 6" total. Fig. 8.16 above determines the same number of events for each station (27 heaviest events) whose heaviest values ranged from 4.4" to 12.5" and their 27th heaviest values ranged from 3.3" to 5.0". This analysis thus allows each station to be equally represented. In other

words, if there is a region-wide increase in heavy events, it should be seen in the sum of all stations. Note too that the period of record here is 135 years vs. 36 years of Howarth et al. Except for three 5-year periods between 1995 and 2014 there is nothing statistically remarkable about the results in Fig. 8.16.

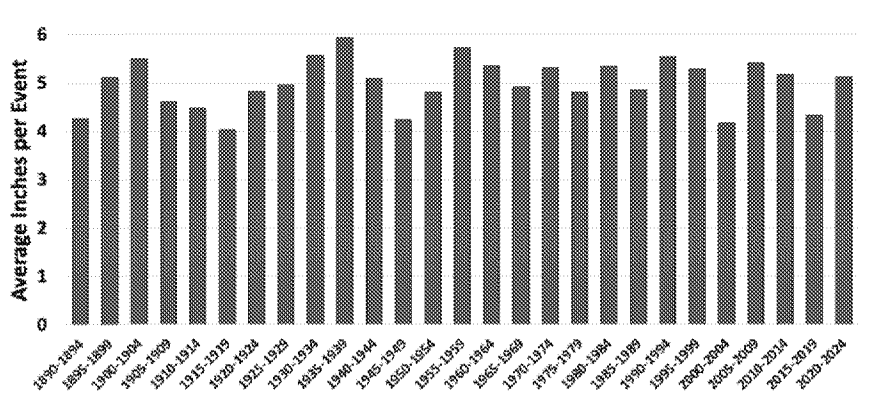


Figure 8.17. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

An interesting aspect of Northeast precipitation is that there has been no change in the amount of precipitation per heaviest event, as shown in Fig. 8.17. The trend is only $+0.02''/\text{decade}$. The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 8.15 and 8.16 suggest that though there was an uptick in the number of events during the period 1995 to 2014; the events, individually, are not becoming more intense.

Jong et al. (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, "The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s." The question then becomes, was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 8.17 where the amount-per-event has remained steady over the 135-year period.

For substantial urban areas there is some evidence to indicate the heaviest rainfall events may be redistributed due to the impact urban infrastructure has on the local weather (e.g., Pielke Sr. et al. 2011, Zhang et al. 2018, Yang et al. 2024). Yang et al. state, "Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with

dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 8.17.

In summary, the evidence from the historical record of extreme precipitation events in the CONUS is generally not consistent from region to region so that inferences regarding trends and their projections are wrought with significant uncertainty. In most regions and perhaps all, it is our opinion that the very nature of the erratic and episodic character of extreme precipitation events renders the discovery of statistically significant changes, including a relationship to CO₂ concentrations, a result yet to be achieved (McKittrick and Christy 2019).

8.4 Summary

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Appendix: Review of IPCC and NCA Findings on Extreme Weather

The sources we review will be denoted as follows:

SREX: The IPCC *Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (2012)

AR5: The IPCC *Fifth Assessment Report Working Group 1* (2013).

AR6: The IPCC *Sixth Assessment Report Working Group 1* (2021).

NCA17: The *US Climate Science Special Report of the Fourth National Climate Assessment* (2017) Volume I Chapter 6.

8A.1 Overview: IPCC Assessment of signal emergence in extreme weather types (AR6 WG1 Table 12.12)

Table 8A.1 reproduces the findings of AR6 Table 12.12 which indicates, for 34 major weather event and impact types, whether a signal of anthropogenic forcing has been detected in the historical record (column 1), whether such a signal is likely to emerge by 2050 under the extreme RCP8.5 scenario (column 2) and whether it is likely to emerge by 2100 under RCP8.5 forcing (column 3). As we discuss in Ch X on attribution there are conflicting messages within the AR6 regarding attribution of extreme weather. This Table is provided here for reference.

Several patterns stand out. First, out of the 34 weather impact categories an anthropogenic signal is asserted with *high confidence* in only four, and with *medium confidence* in a further four. For the rest the IPCC does not claim to have detected anthropogenic drivers. Of the four *high confidence* assertions, two are for changes in average temperatures (air and ocean) hence are not measures of extreme weather. Also two of the four *medium confidence* assertions are related to ocean chemistry and thus are likewise not related to extreme weather. The IPCC does not assert a human influence on many non-temperature weather features such as wind, precipitation, flooding, drought etc.

Second, as shown in columns 2 and 3 the IPCC expects very few such signals to emerge this century *even under the most extreme forcing scenario*. As we discuss in Section 4.2 the RCP8.5 scenario is an implausible high-end storyline, it is not a "base case" or business-as-usual projection. Yet even still most weather impacts are not expected to exhibit an anthropogenic signal this century. As will be clear from the underlying report text, natural variability dominates patterns of extreme weather systems and simplistic assertions of trend detection are frequently undermined by regional heterogeneity and trends reversals over time.

Climate Impact Driver Type	Climate Impact Driver Category	Already Emerged in the Historical Record?	Emerging by 2050 in Most Extreme CO2 Emissions Scenario?	Emerging by 2100 in Most Extreme CO2 Emissions Scenario?
Heat & Cold	Average air temperature	YES in most regions	YES	YES
	More heat extremes	YES in most regions	YES in land regions	YES
	Fewer cold extremes	YES in a few regions	YES in many regions	YES
	Less frost	NO	NO	NO
Wet & Dry	Average Precip. (Increase or Decrease)	NO	YES (incr) YES (decr)	YES (incr) YES (decr)
	River flooding	NO	NO	NO
	Heavy precip & pluvial flood	NO	NO	YES in a few regions
	Landslide	NO	NO	NO

	Aridity	NO	NO	NO
	Hydrologic Drought	NO	NO	NO
	Agricultural & ecological drought	NO	NO	NO
	Fire weather	NO	NO	NO
Wind	Average wind speed	NO	NO	NO
	Severe wind storm	NO	NO	NO
	Tropical cyclone	NO	NO	NO
	Sand and dust storm	NO	NO	NO
Snow and Ice	Snow, glacier & ice sheet	NO	YES in a few regions	YES Arctic snow
	Permafrost	YES	YES	YES
	Lake & river ice	NO	YES	YES
	Arctic sea ice	YES	YES	YES
	Antarctic sea ice	NO	YES	YES
	Heavy snowfall and ice storm	NO	NO	NO
	Hail	NO	NO	NO
	Snow avalanche	NO	NO	NO
Coastal	Relative sea level	NO	YES	YES
	Coastal flood	NO	NO	NO
	Coastal erosion	NO	NO	NO
Open Ocean	Average ocean temperature	YES	YES	YES
	Marine heat wave	NO	NO	NO
	Ocean acidity	NO	YES	YES
	Ocean salinity	YES	YES	YES
	Dissolved oxygen	YES (Pacific & S. Ocean)	YES	YES
Other	Air pollution weather	NO	NO	NO
	Solar or IR radiation at surface	NO	NO	NO

Table 8A.1. IPCC AR6 summary of the probable emergence of an anthropogenic signal above natural climate variability for all global or regional “climate impact drivers” (CIDs) of concern for humans and ecosystems in response to increasing atmospheric greenhouse gas concentrations (primarily CO₂). Source: Table adapted from report of Working Group I, Table 12.12). Red = high confidence; yellow = medium confidence; green = no anthropogenic signal detectable above natural variability (50% confidence).

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Taking wind as an example, the IPCC claims that an anthropogenic signal has not emerged in average wind speeds, severe wind storms, tropical cyclones or sand and dust storms, nor is one expected to emerge this century even under an extreme emissions scenario. The same applies to drought and fire weather. This table alone suffices to illustrate the gap between IPCC expert assessment of extreme weather and discussions of extreme weather in the popular press. As we show below the Table reflects longstanding conclusions of the IPCC and other assessment bodies. In the next few sections we will simply present without comment excerpts from past assessment reports.

Notes: in these excerpts bold-face emphasis is added. Italicized emphasis on *confidence* terms is in the original sources. Citations contained in quoted text can be found in the underlying reports but are not reproduced here.

8A.2 Flooding

SREX (p. 176)

In the United States and Canada during the 20th century and in the early 21st century, **there is no compelling evidence for climate-driven changes in the magnitude or frequency of floods.**

AR5 (p. 214)

AR4 WGI Chapter 3 (Trenberth et al., 2007) did not assess changes in floods but AR4 WGII concluded that **there was not a general global trend in the incidence of floods** (Kundzewicz et al., 2007). SREX went further to suggest that there was low agreement and thus *low confidence* at the global scale regarding changes in the magnitude or frequency of floods or even the sign of changes.

AR5 WGII assesses floods in regional detail accounting for the fact that trends in floods are strongly influenced by changes in river management (see also Section 2.5.2). Although the most evident flood trends appear to be in northern high latitudes, where observed warming trends have been largest, in some regions no evidence of a trend in extreme flooding has been found, for example, over Russia based on daily river discharge (Shiklomanov et al., 2007). Other studies for Europe (Hannaford and Marsh, 2008; Renard et al., 2008; Petrow and Merz, 2009; Stahl et al., 2010) and Asia (Jiang et al., 2008; Delgado et al., 2010) show evidence for upward, downward or no trend in the magnitude and frequency of floods, so that there is currently no clear and widespread evidence for observed changes in flooding except for the earlier spring flow in snow-dominated regions (Seneviratne et al., 2012).

In summary, **there continues to be a lack of evidence and thus *low confidence* regarding the sign of trend in the magnitude and/or frequency of floods on a global scale.**

AR6 (Ch 11 p. 1568)

The SREX (Seneviratne et al., 2012) assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report (Hartmann et al., 2013). The SR15 (Hoegh-Guldberg et al., 2018) found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. **While the number of studies on flood trends has increased since the AR5 report, and there were also new analyses after the release of SR15 (Berghuijs et al., 2017; Blöschl et al., 2019; Gudmundsson et al., 2019), hydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.**

In summary, the seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). **Confidence about peak flow trends over past decades on the global scale is low, but there are regions experiencing increases**, including parts of Asia, southern South America, the northeast USA, northwestern Europe, and the Amazon, **and regions experiencing decreases**, including parts of the Mediterranean, Australia, Africa, and the southwestern USA.

US NCA17 pp. 240-41:

"The IPCC AR5 did not attribute changes in flooding to anthropogenic influence nor report detectable changes in flooding magnitude, duration, or frequency. Trends in extreme high values of streamflow are mixed across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude but does not provide robust evidence that these trends are attributable to human influences...

The complex mix of processes complicates the formal attribution of observed flooding trends to anthropogenic climate change and suggests that additional scientific rigor is needed in flood attribution studies. As noted above, precipitation increases have been found to strongly influence changes in flood statistics. However, in U.S. regions, **no formal attribution of precipitation changes to anthropogenic forcing has been made so far, so indirect attribution of flooding changes is not possible. Hence, no formal attribution of observed flooding changes to anthropogenic forcing has been claimed.**"

8A.3 Heatwaves

AR5 (p. 212 WG1)

Table 2.13 shows that there has been a *likely* increasing trend in the frequency of heatwaves since the middle of the 20th century in Europe and Australia and across much of Asia where there are sufficient data. However, confidence on a global scale is *medium* owing to lack of studies over Africa and South America but also in part owing to differences in trends depending on how heatwaves are defined (Perkins et al., 2012). Using monthly means as a proxy for heatwaves Coumou et al. (2013) and Hansen et al. (2012) indicate that record-breaking temperatures in recent decades substantially exceed what would be expected by chance but caution is required when making inferences between these studies and those that deal with multi-day events and/or use more complex definitions for heatwave events. **There is also evidence in some regions that periods prior to the 1950s had more heatwaves (e.g., over the USA, the decade of the 1930s stands out and is also associated with extreme drought conditions** (Peterson et al., 2013) whereas conversely in other regions heatwave trends may have been underestimated owing to poor quality and/or consistency of data (e.g., Della-Marta et al. (2007a) over Western Europe; Kuglitsch et al. (2009, 2010) over the Mediterranean). Recent available studies also suggest that the number of cold spells has reduced significantly since the 1950s (Donat et al., 2013a, 2013c).

In summary, new analyses continue to support the AR4 and SREX conclusions that since about 1950 it is *very likely* that the numbers of cold days and nights have decreased and the numbers of warm days and nights have increased overall on the global scale, that is, for land areas with sufficient data. It is *likely* that such changes have also occurred across most of North America, Europe, Asia and Australia.

NCA17 (pp. 190-191)

Changes in warm extremes are more nuanced than changes in cold extremes. For instance, **the warmest daily temperature of the year increased in some parts of the West over the past century (Figure 6.3), but there were decreases in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net decrease** (Table 6.2), most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]). The decreases in the eastern half of [the] Nation, particularly in the Great Plains, are mainly tied to the unprecedented summer heat of the 1930s Dust Bowl era, which was exacerbated by land-surface feedbacks driven by springtime precipitation deficits and land mismanagement. However, anthropogenic aerosol forcing may also have reduced summer temperatures in the Northeast and Southeast from the early 1950s to the mid-1970s, and agricultural intensification may have suppressed the hottest extremes in the Midwest.

Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). **Heat waves (6-day periods**

with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter (Figure 6.4). As with warm daily temperatures, heat wave magnitude reached a maximum in the 1930s.

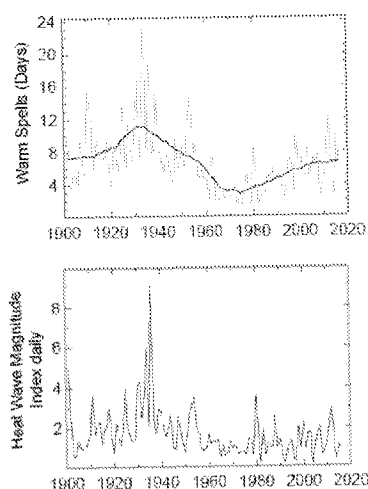


Figure 8.1: US Heat waves since 1900. Source: NCA17 Figure 6.4

AR6 (p. 1550)

In North America (Table 11.19), there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, **while there are more contrasting trends in the annual maximum daily temperatures** in parts of the USA (Figure 11.9; Lee et al., 2014; van Oldenborgh et al., 2019; Dunn et al., 2020).

8A.4 Extreme snowfall events

Note: extreme snowfall events in the US northeast are assessed in relation to winter Extratropical Cyclone (ETC) activity.

AR6 Ch 11. p. 1593

There is *high confidence* that snowfall associated with winter ETCs will decrease in the future, because increases in tropospheric temperatures lead to a lower proportion of precipitation falling as snow (O’Gorman, 2014; Rhoades et al., 2018; Zarzycki, 2018). However, there is *medium confidence* that extreme snowfall events associated with winter ETCs will change little in regions where snowfall will be supported in the future (O’Gorman, 2014; Zarzycki, 2018).

8A.5 Extreme precipitation

SREX (p. 142)

Recent studies have updated the assessment of the AR4, with more regional results now available (Table 3-2). Overall, this additional evidence confirms that **more locations and studies show an increase than a decrease in extreme precipitation, but that there are also wide regional and seasonal variations**, and trends in many regions are not statistically significant (Table 3-2)... Based on station data from Canada, the United States, and Mexico, Peterson et al. (2008a) reported that heavy precipitation has been increasing over 1950-2004, as well as the average amount of precipitation falling on days with precipitation.

AR5 (pp. 213-14)

In summary, further analyses continue to support the AR4 and SREX conclusions that **it is likely that since 1951 there have been statistically significant increases in the number of heavy precipitation events (e.g., above the 95th percentile) in more regions than there have been statistically significant decreases, but there are strong regional and subregional variations in the trends**. In particular, many regions present statistically non-significant or negative trends, and, where seasonal changes have been assessed, there are also variations between seasons (e.g., more consistent trends in winter than in summer in Europe). The overall most consistent trends towards heavier precipitation events are found in central North America (very likely increase) but assessment for Europe shows likely increases in more regions than decreases.

AR6 (p. 1560)

In North America, there is robust evidence that the magnitude and intensity of extreme precipitation has *very likely* increased since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 (Sun et al., 2020, also Figure 11.13). There is, however, regional diversity. In Canada, there is a lack of detectable trends in observed annual maximum daily (or shorter duration) precipitation (Shephard et al., 2014; Mekis et al., 2015; Vincent et al., 2018).

NCA17 pp. 213-14:

Detectability of trends (compared to internal variability) for a number of precipitation metrics over the continental United States has been examined; **however, trends identified for the U.S. regions have not been clearly attributed to anthropogenic forcing**. One study concluded that increasing precipitation trends in some north-central U.S. regions and the extreme annual anomalies there in 2013 were at least partly attributable to the combination of anthropogenic and natural forcing... **Based on current evidence, it is concluded that detectable but not attributable increases in mean precipitation have occurred over parts of the central United States**. Formal detection-attribution studies indicate a human contribution to extreme precipitation increases over the continental United States, but confidence is *low* based on those studies alone due to the short observational period, high natural variability, and model uncertainty.

In summary, based on available studies, it is concluded that for the continental United States there is *high confidence* in the detection of extreme precipitation increases, while there is *low confidence* in attributing the extreme precipitation changes purely to anthropogenic forcing.

8A.6 Tornadoes and severe convective storms

IPCC AR6 Sct. 11.7.3, p. 1594

Severe convective storms are convective systems that are associated with extreme phenomena such as tornadoes, hail, heavy precipitation (rain or snow), strong winds, and lightning.

The assessment of changes in severe convective storms in SREX (Chapter 3, Seneviratne et al., 2012) and AR5 (Chapter 12, Collins et al., 2013) is limited and focused mainly on tornadoes and hail storms. The SREX assessed that there is *low confidence* in observed trends in tornadoes and hail because of data inhomogeneities and inadequacies in monitoring systems. Subsequent literature assessed in the Climate Science Special Report (Kossin et al., 2017) led to the assessment of the observed tornado activity over the 2000s in the USA, with a decrease in the number of days per year with tornadoes and an increase in the number of tornadoes on these days (*medium confidence*). However, there is *low confidence* in past trends for hail and severe thunderstorm winds. Climate models consistently project environmental changes that would support an increase in the frequency and intensity of severe thunderstorms that combine tornadoes, hail, and winds (*high confidence*), but there is *low confidence* in the details of the projected increase.

... In summary, because the definition of severe convective storms varies depending on the literature and the region, it is not straightforward to make a synthesizing view of observed trends in severe convective storms in different regions. In particular, observational trends in tornadoes, hail, and lightning associated with severe convective storms are not robustly detected due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant, but their variability of occurrence has increased since the 1970s, particularly over the 2000s, with a decrease in the number of days per year, and an increase in the number of tornadoes on these days (*high confidence*). Detected tornadoes have also increased in Europe, but the trend depends on the density of observations.

... It is extremely difficult to detect differences in time and space of severe convective storms (Kunkel et al., 2013). Although some ingredients that are favourable for severe thunderstorms have increased over the years, others have not; thus, overall, changes in the frequency of environments favourable for severe thunderstorms have not been statistically significant... For hailstorms, such as those that caused disasters in the USA in 2018, detection of the role of climate change in changing hail storms is more difficult, because hail storms are not, in general, directly simulated by convection-permitting models and not adequately represented by the environmental parameters of coarse-resolution GCMs (Mahoney, 2020).

In summary, it is extremely difficult to detect and attribute changes in severe convective storms. There is limited evidence that extreme precipitation associated with severe convective storms has increased in some cases.

8A.7 Hurricanes and Tropical Cyclones

SREX (p. 159):

There have been no significant trends observed in global tropical cyclone frequency records, including over the present 40-year period of satellite observations (e.g., Webster et al., 2005). Regional trends in tropical cyclone frequency have been identified in the North Atlantic, but the fidelity of these trends is debated (Holland and Webster, 2007; Landsea, 2007; Mann et al., 2007a). Different methods for estimating undercounts in the earlier part of the North Atlantic tropical cyclone record provide mixed conclusions (Chang and Guo, 2007; Mann et al., 2007b; Kunkel et al., 2008; Vecchi and Knutson, 2008). Regional trends have not been detected in other oceans (Chan and Xu, 2009; Kubota and Chan, 2009; Callaghan and Power, 2011). **It thus remains uncertain whether any observed increases in tropical cyclone frequency on time scales longer than about 40 years are robust**, after accounting for past changes in observing capabilities (Knutson et al., 2010).

AR5 (pp. 216-17):

Current data sets indicate no significant observed trends in global tropical cyclone frequency over the past century and it remains uncertain whether any reported long-term increases in tropical cyclone frequency are robust, after accounting for past changes in observing capabilities (Knutson et al., 2010). **No robust trends in annual numbers of tropical storms, hurricanes and major hurricanes counts have been identified** over the past 100 years in the North Atlantic basin. Measures of land-falling tropical cyclone frequency (Figure 2.34) are generally considered to be more reliable than counts of all storms which tend to be strongly influenced by those that are weak and/or short lived. Callaghan and Power (2011) find a statistically significant decrease in Eastern Australia land-falling tropical cyclones since the late 19th century although including 2010/2011 season data this trend becomes non-significant (i.e., a trend of zero lies just inside the 90% confidence interval). Significant trends are not found in other oceans on shorter time scales (Chan and Xu, 2009; Kubota and Chan, 2009; Mohapatra et al., 2011; Weinkle et al., 2012), although Grinsted et al. (2012) find a significant positive trend in eastern USA using tide-gauge data from 1923–2008 as a proxy for storm surges associated with land-falling hurricanes. Differences between tropical cyclone studies highlight the challenges that still lie ahead in assessing long-term trends.

In summary, this assessment does not revise the SREX conclusion of *low confidence* that any reported long-term (centennial) increases in tropical cyclone activity are robust, after accounting for past changes in observing capabilities. More recent assessments indicate that **it is unlikely that annual numbers of tropical storms, hurricanes and major hurricanes counts have increased over the past 100 years in the North Atlantic basin**. Evidence, however, is for a virtually certain increase in the frequency and intensity of the strongest tropical cyclones since the 1970s in that region.

AR6 (p. 1585)

There is low confidence in most reported long-term (multidecadal to centennial) trends in TC frequency- or intensity-based metrics due to changes in the technology used to collect the best-track data. This should not be interpreted as implying that no physical (real) trends exist, but rather as indicating that either the quality or the temporal length of the data is not adequate to provide robust trend detection statements, particularly in the presence of multidecadal variability.

There are previous and ongoing efforts to homogenize the best-track data (Elsner et al., 2008; Kossin et al., 2013, 2020; Choy et al., 2015; Landsea, 2015; Emanuel et al., 2018) and there is substantial literature that finds positive trends in intensity-related metrics in the best-track

during the “satellite period”, which is generally limited to the past ~40 years (Kang and Elsner, 2012; Kishtawal et al., 2012; Kossin et al., 2013, 2020; Mei and Xie, 2016; Zhao et al., 2018; Tauvale and Tsuboki, 2019). **When best-track trends are tested using homogenized data, the intensity trends generally remain positive, but are smaller in amplitude** (Kossin et al., 2013; Holland and Bruyère, 2014). **Kossin et al. (2020) extended the homogenized TC intensity record to the period 1979–2017 and identified significant global increases in major TC exceedance probability of about 6% per decade.** In addition to trends in TC intensity, there is evidence that TC intensification rates and the frequency of rapid intensification events have increased within the satellite era (Kishtawal et al. 2012; Balaguru et al., 2018; Bhatia et al., 2018). The increase in intensification rates is found in the best-track as well as the homogenized intensity data.

A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows no trend in the frequency of U.S. landfall events (Knutson et al., 2019).

Note: The **Underlined** text referenced a study (Kossin et al. 2020) that later retracted a portion of its findings. The authors assembled a data set on global TC incidence spanning 1979 to 2017. They claimed that the global fraction of TCs reaching major status (Cat 3–5) rose from 27% in the 1979–1997 interval to 31% in the 1998–2017 interval and the difference was statistically significant. Closer examination of their results however showed a significant increase was only observed in the North Atlantic (18% to 34%) whereas in every other basin (Eastern Pacific, Western Pacific, North Indian, South Indian, South Pacific) the differences were not statistically significant. Kossin et al. issued a Correction (<https://www.pnas.org/doi/10.1073/pnas.2021573117>). The revised version said that the global probability of observing a major TC was 34% in the 1979 to 1997 interval rising to 37% in the later period and the evidence for statistical significance was now weaker, although the authors claimed that the correction did not affect their conclusions.

8A.8 Droughts

US NCA17 REPORT (Ch. 8, Wehner et al. 2017)

p. 231:

Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the 1930s remains the benchmark drought and extreme heat event in the historical record (very high confidence). **While by some measures drought has decreased over much of the continental United States in association with long-term increases in precipitation, neither the precipitation increases nor inferred drought decreases have been confidently attributed to anthropogenic forcing.**

The human effect on recent major U.S. droughts is complicated. Little evidence is found for a human influence on observed precipitation deficits, but much evidence is found for a human influence on surface soil moisture deficits due to increased evapotranspiration caused by higher temperatures. (*High confidence*)

p. 233:

Drought is, of course, directly connected to seasonal precipitation totals. Figure 7.1 shows detectable observed recent changes in seasonal precipitation. In fact, the increases in

observed summer and fall precipitation are at odds with the projections in Figure 7.5. **As a consequence of this increased precipitation, drought statistics over the entire CONUS have declined.**

SREX (p. 170)

From a paleoclimate perspective recent droughts are not unprecedented, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia (Jansen et al., 2007). Recent studies extend this observation to African and Indian droughts (Sinha et al., 2007; Shanahan et al., 2009): much more severe and longer droughts occurred in the past centuries with widespread ecological, political, and socioeconomic consequences. Overall, these studies confirm that in the last millennium several extreme droughts have occurred (Breda and Badeau, 2008; Kallis, 2008; Büntgen et al., 2010).

In North America, there is *medium confidence* that there has been an overall slight tendency toward less dryness (wetting trend with more soil moisture and runoff; Table 3-2), although analyses for some subregions also indicate tendencies toward increasing dryness. This assessment is based on several lines of evidence, including simulations with different hydrological models as well as PDSI and CDD estimates (Alexander et al., 2006; Andreadis and Lettenmaier, 2006; van der Schrier et al., 2006a; Kunkel et al., 2008; Sheffield and Wood, 2008a; Dai, 2011).

The most severe droughts in the 20th century have occurred in the 1930s and 1950s, where the 1930s Dust Bowl was most intense and the 1950s drought most persistent (Andreadis et al., 2005) in the United States, while in Mexico the 1950s and late 1990s were the driest periods. Recent regional trends toward more severe drought conditions were identified over southern and western Canada, Alaska, and Mexico, with subregional exceptions (Dai, 2011).

SREX (p. 172)

Overall, though new studies have furthered the understanding of the mechanisms leading to drought, there is still relatively limited evidence to provide an attribution of observed changes, in particular given the issues associated with the availability of observational data (Section 3.2.1) and the definition and computation of drought indicators (Box 3-3). This latter point was mostly identified in post-AR4 studies (Box 3-3). Moreover, regions where consistent increases in drought are identified (see ‘Observed Changes’) are only partly consistent with those where projections indicate an enhancement of drought conditions in coming decades (see next paragraphs). We thus assess that there is *medium confidence* (see also Section 3.1.5) that anthropogenic influence has contributed to some changes in the drought patterns observed in the second half of the 20th century, based on its attributed impact on precipitation and temperature changes (though temperature can only be indirectly related to drought trends; see Box 3-3). However **there is *low confidence* in the attribution of changes in droughts at the level of individual regions.**

AR5 (pp. 214-215)

Based on evidence since AR4, SREX concluded that there were not enough direct observations of dryness to suggest high confidence in observed trends globally, although there was *medium confidence* that since the 1950s some regions of the world have experienced more intense and longer droughts. The differences between AR4 and SREX are due primarily to analyses

post-AR4, differences in how both assessments considered drought and updated IPCC uncertainty guidance.

Because drought is a complex variable and can at best be incompletely represented by commonly used drought indices, discrepancies in the interpretation of changes can result. For example, Sheffield and Wood (2008) found decreasing trends in the duration, intensity and severity of drought globally. Conversely, Dai (2011a,b) found a general global increase in drought, although with substantial regional variation and individual events dominating trend signatures in some regions (e.g., the 1970s prolonged Sahel drought and the 1930s drought in the USA and Canadian Prairies). Studies subsequent to these continue to provide somewhat different conclusions on trends in global droughts and/or dryness since the middle of the 20th century (Sheffield et al., 2012; Dai, 2013; Donat et al., 2013c; van der Schrier et al., 2013).

In summary, the current assessment concludes that there is not enough evidence at present to suggest more than low confidence in a global-scale observed trend in drought or dryness (lack of rainfall) since the middle of the 20th century, owing to lack of direct observations, geographical inconsistencies in the trends, and dependencies of inferred trends on the index choice. Based on updated studies, AR4 conclusions regarding global increasing trends in drought since the 1970s were probably overstated. However, it is *likely* that the frequency and intensity of drought has increased in the Mediterranean and West Africa and decreased in central North America and north-west Australia since 1950.

AR6 (Drought, Observed trends, Section 11.6.2, pp. 1573-75)

p. 1573

Strong precipitation deficits have been recorded in recent decades in the Amazon (2005, 2010), south-western China (2009–2010), south-western North America (2011–2014), Australia (1997–2009), California (2014), the middle East (2012–2016), Chile (2010–2015), the Great Horn of Africa (2011), among others (van Dijk et al., 2013; Mann and Gleick, 2015; Rowell et al., 2015; Marengo and Espinoza, 2016; Dai and Zhao, 2017; Garreaud et al., 2017, 2020; Marengo et al., 2017; Brito et al., 2018; Cook et al., 2018). **Global studies generally show no significant trends in SPI time series** (Orlowsky and Seneviratne, 2013; Spinoni et al., 2014), **and in derived drought frequency and severity data** (Spinoni et al., 2019), with very few regional exceptions (Section 11.9 and Figure 11.17).

p. 1574

For AR6 regions, several studies suggest an increase in the frequency and areal extent of soil moisture deficits, with examples in East Asia (Cheng et al., 2015; Y. Qin et al., 2015; Jia et al., 2018), Western and Central Europe (Trnka et al., 2015b), and the Mediterranean (Hanel et al., 2018; Moravec et al., 2019; Markonis et al., 2021). **Nonetheless, some analyses also show no long-term trends in soil drying in some AR6 regions – for example, in Eastern North America (Park Williams et al., 2017) and Central North America** (Seager et al., 2019), as well as in North Eastern Africa (Kew et al., 2021).

There is evidence based on streamflow records of increased hydrological droughts in East Asia (D. Zhang et al., 2018) and southern Africa (Gudmundsson et al., 2019). **In areas of Western and Central Europe and Northern Europe, there is no evidence of changes in the severity of hydrological droughts since 1950** based on flow reconstructions (Caillouet et al., 2017; Barker et al., 2019) and observations (Vicente-Serrano et al., 2019). **In North**

America, depending on the methods, datasets and study periods, there are differences between studies that suggest an increase (Shukla et al., 2015; Udall and Overpeck, 2017) versus a decrease in hydrological drought frequency (Mo and Lettenmaier, 2018), but in general there is strong spatial variability (Poshtiri and Pal, 2016). Streamflow observation reference networks of near-natural catchments have also been used to isolate the effect of climate trends on hydrological drought trends in a few regions, but these show limited trends in Northern Europe and Western and Central Europe (Stahl et al., 2010; Bard et al., 2015; Harrigan et al., 2018), North America (Dudley et al., 2020) and most of Australia, with the exception of Eastern and Southern Australia (X.S. Zhang et al., 2016).

p. 1575

Few AR6 regions show observed increases in meteorological drought (Section 11.9), mostly in Africa and South America (NES: *high confidence*; WAF, CAF, ESAF, SAM, SWS, SSA, SAS: *medium confidence*); a few others show a decrease (WSB, ESB, NAU, CAU, NEU, CNA: *medium confidence*). There are stronger signals indicating observed increases in agricultural and ecological drought (Section 11.9), which highlights the role of increased [evapotranspiration], driven by increased [Atmospheric Evaporative Demand], for these trends (Sections 11.6.2.3, 11.6.2.5). Past increases in agricultural and ecological droughts are found on all continents and several regions (WAF, CAF, WSAF, ESAF, WCA, ECA, EAS, SAU, MED, WCE, NES: *medium confidence*), while decreases are found only in one AR6 region (NAU: *medium confidence*). The more limited availability of datasets makes it more difficult to assess historical trends in hydrological drought at regional scale (Section 11.9). Increasing (MED: *high confidence*; WAF, EAS, SAU: *medium confidence*) and decreasing (NEU, SES: *medium confidence*) trends in hydrological droughts have only been observed in a few regions.

AR6 on Attribution (p. 1577)

There are only two AR6 regions in which there is at least *medium confidence* that human-induced climate change has contributed to changes in meteorological droughts (Section 11.9). In South-western South America (SSW), there is *medium confidence* that human-induced climate change has contributed to an increase in meteorological droughts (Boisier et al., 2016; Garreaud et al., 2020), while in Northern Europe (NEU), there is *medium confidence* that it has contributed to a decrease in meteorological droughts (Gudmundsson and Seneviratne, 2016) (Section 11.9). **In other AR6 regions, there is inconclusive evidence in the attribution of long-term trends, but a human contribution to single meteorological events or subregional trends has been identified in some instances... In North America, the human influence on precipitation deficits is complex (Wehner et al., 2017), with low confidence in the attribution of long-term changes in meteorological drought in AR6 regions.**

12 Mortality from temperature extremes

Changes in temperature extremes are among the most certain impacts expected in a warming globe -- extreme heat events are expected to become more frequent while extreme cold events become less frequent. This pattern is evident in the historical period (as discussed in Section XX) and is expected to intensify with continued warming.

Mortality during heat extremes is typically caused by heat stroke and heat exhaustion, while mortality during cold extremes is typically caused by hypothermia and heart strain. It is well known that global mortality is substantially greater for extreme cold than for extreme heat.^{1,2}

Specific to the U.S., extreme heat and extreme cold both kill hundreds of people each year.; however, different approaches to assessing heat/cold mortality produces different results. The Center for Disease Control (CDC) National Center for Health Statistics Compressed Mortality Database, which is based on death certificates, indicates that about twice as many people die of “excessive cold” conditions in a given year than of “excessive heat.”^{3,4}

A 2015 epidemiological study of deaths in published in *The Lancet* found that cold-related deaths in the U.S. were about a factor of fifteen higher than heat-related deaths.⁵ However, the study did not adjust for the seasonal cycle in mortality rates, which tend to increase during the winter months due to non-weather factors like influenza.⁶ A more recent paper found that 86% of temperature-related deaths in the U.S. are due to cold-related mortality.⁷

¹ Qi Zhao et al., “Global, Regional, and National Burden of Mortality Associated with Non-Optimal Ambient Temperatures from 2000 to 2019: A Three-Stage Modelling Study,” *The Lancet Planetary Health* 5, no. 7 (July 2021), [https://doi.org/10.1016/s2542-5196\(21\)00081-4](https://doi.org/10.1016/s2542-5196(21)00081-4).

² <https://ourworldindata.org/part-one-how-many-people-die-from-extreme-temperatures-and-how-could-this-change-in-the-future>

³ Brett R. Scheffers et al., “The Broad Footprint of Climate Change from Genes to Biomes to People,” *Science* 354, no. 6313 (November 11, 2016): aaf7671, <https://doi.org/10.1126/science.aaf7671>.

⁴ Rachel H. Alinsky, Scott E. Hadland, J. Deanna Wilson, Pamela A. Matson, and Brendan Saloner, “Trends in Polysubstance Overdose Deaths Involving Opioids, Stimulants, and Benzodiazepines by Race and Ethnicity in the US, 2007-2021,” *JAMA Network Open* 7, no. 3 (March 2024): e238249, <https://doi.org/10.1001/jamanetworkopen.2024.8249>.

⁵ Lancet Commission on Climate and Health, “Health and Climate Change: Policy Responses to Protect Public Health,” *The Lancet* 386, no. 10006 (November 7, 2015): 1861–1914, [https://doi.org/10.1016/S0140-6736\(15\)60854-6](https://doi.org/10.1016/S0140-6736(15)60854-6).

⁶ Bob Henson, “Which Kills More People: Extreme Heat or Extreme Cold?” *Weather Underground*, January 22, 2019, <https://www.wunderground.com/cat6/Which-Kills-More-People-Extreme-Heat-or-Extreme-Cold>.

⁷ Tarik Benmarhnia et al., “Deaths Attributable to Heat and Cold: Comparison of Data Sources and Evaluation of Inconsistencies,” *GeoHealth* 8, no. 3 (March 2024): e2023GH000799, <https://doi.org/10.1029/2023GH000799>.

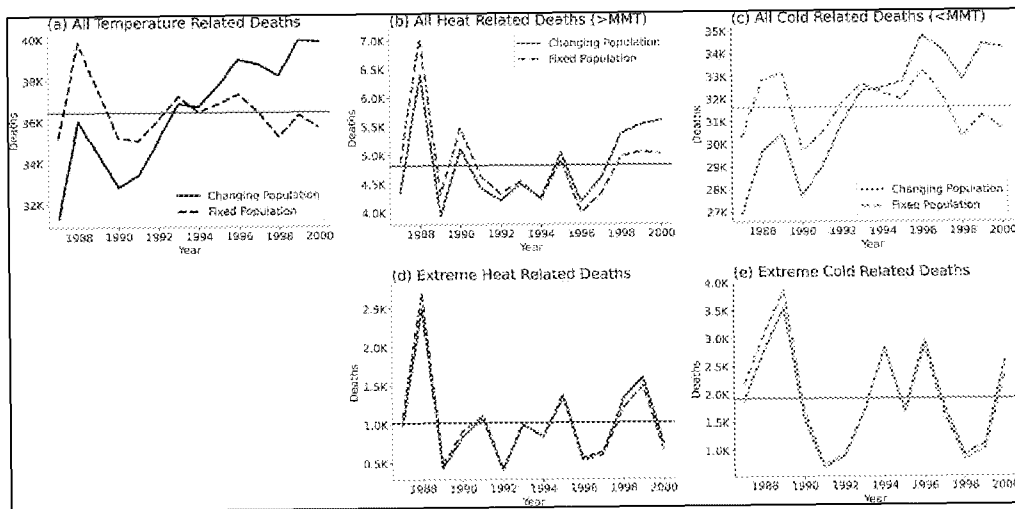


Figure 12.1: Time series of temperature-related deaths across all 106 cities. (a) The solid line represents total temperature-related deaths, while the dashed line indicates temperature-related deaths with a fixed population (average population from the 1987–2000 period). (b) Similar to (a), but for heat-related deaths. (c) Similar to (a), but for cold-related deaths. (d) Time series of deaths occurring in temperatures above the 97.5th percentile. (e) Similar to (d), but for temperatures below the 2.5th percentile. From <https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2023GH000799>

The IPCC AR6 Working Group 2 Chapter 16.2.3.5 states how heat-related mortality is declining over time:⁸

“Heat-attributable mortality fractions have declined over time in most countries owing to general improvements in health care systems, increasing prevalence of residential air conditioning, and behavioral changes. These factors, which determine the susceptibility of the population to heat, have predominated over the influence of temperature change.”

A 2011 study of 40 major US cities between 1975 and 2004, found that heat wave mortality had decreased, in spite of rising temperatures, due to adaptation.⁹

By reducing mortality from cold events and adapting to heat extremes, rising temperatures are associated with a net saving of lives.

It is both disappointing and telling to see how the IPCC misrepresents the situation in its AR6 Synthesis report. Section A.2.5 of that document states: “In all regions increases in extreme heat

⁸ B. O'Neill et al., “Key Risks Across Sectors and Regions,” in *Climate Change 2022: Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, CH: Intergovernmental Panel on Climate Change, 2021), 2411–2538.

⁹ Keith T. Ingram, Carolyn W. Furman, and John W. Jones, “Climate Change Impact and Adaptation Assessment: A Guide for Coastal Resources Managers,” *Weather, Climate, and Society* 3, no. 4 (October 2011): 234–249, <https://doi.org/10.1175/WCAS-D-11-00055.1>.

events have resulted in human mortality and morbidity (*very high confidence*).” But it is silent on the larger decline of deaths during extreme cold events.

Mortality risks and energy costs

A 2016 study of US long term mortality risks associated with temperature variations (Barreca et al. 2016) showed that increases in mortality across the US are associated both with cold weather and hot weather. But over time, the introduction of electricity and the adoption of central heating and air conditioning (AC) dramatically reduced both risks, especially those associated with hot weather. Prior to 1960, a day above 90°F (32°C) added 2.2 percent to the average mortality risk rate, but after 1960 the same weather added only 0.3 percent to mortality risk, an 85 percent reduction. Prior to 1960 temperatures below 39°F (4°C) added about 1 percent to mortality risk but after 1960 the same weather only added about half that amount. Adaptation through conventional household improvements dramatically reduced public vulnerability to weather extremes. The entire reduction in hot weather mortality was attributable to widespread adoption of indoor AC, which depended on the availability of reliable and affordable electricity.

The corollary of this finding is that the use of heating and cooling systems depends on energy being affordable. Doremus et al. (2022) showed that wealthy and poor households in the US adjust their energy expenditures at similar rates in response to moderate temperature swings, but not in response to extreme temperature swings. When temperatures swing to very cold levels (< 5°C) energy spending in high-income households rises by 1.2 percent but in low-income households by only 0.5 percent. On very hot days (>30°C) electricity spending in high-income households rises by 0.5 percent but does not change at all in low-income households. The latter result is observed even in subsamples where all households have AC. The implication is that even with widespread adoption of home heating and cooling systems, inability to afford energy leaves low-income households exposed to weather extremes.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro, “Adapting to climate change: The remarkable decline in the US temperature mortality relationship over the twentieth century,” *Journal of Political Economy*, 2016, 124 (1), 105–159.

J.M. Doremus, I. Jacqz and S. Johnston (2022), “Sweating the energy bill: Extreme weather, poor households, and the energy spending gap.” *Journal of Environmental Economics and Management*, doi: <https://doi.org/10.1016/j.jeem.2022.102609> .

13 Climate change, the economy and the Social Cost of Carbon

13.1 Climate change and economic growth

13.1.1 Overview: climate is a relatively minor issue for a modern economy

It has long been noted that economies tend to do poorly in very cold and very hot regions, with the optimum somewhere in between (Nordhaus 2006). Temperature-sensitive economic activity migrates, whenever possible, to where it is best suited, and society always adapts to the local climate. Based in part on these observations, in 1992 Thomas Schelling, then President of the American Economic Association, argued that any effects climate change on US economic activity would be small relative to the many other changes that would happen.

... Manufacturing rarely depends on climate, and where temperature and humidity used to make a difference, air conditioning has intervened. When Toyota chooses among Ohio, Alabama, and Southern California for locating an automobile assembly, geographical considerations are important, but not because of climate... Finance is little affected by climate; similarly for health care, or education, or broadcasting. Transportation can be affected, but improvements in all-weather landing and take-off in the last 30 years are greater than any differences that climate makes. If the average effect is a warming, iced waterways and snow removal may decline in importance. Construction is affected, mainly by cold, and if the average effect is in the direction of warming, construction may benefit slightly.

It is really agriculture that is affected. But even if agricultural productivity declined by a third over the next half century, the per capita GNP we might have achieved by 2050 we would achieve only in 2051. ...

I conclude that in the United States, and probably Japan, Western Europe, and other developed countries, the impact on economic output will be negligible and unlikely to be noticed.

(Schelling 1992, emphasis added)

Thirty years later virtually the identical point was made by the IPCC itself in the Fifth Assessment Report:

For most economic sectors, the impact of climate change will be small relative to the impacts of other drivers. Changes in population, age, income, technology, relative prices, lifestyle, regulation, governance, and many other aspects of socioeconomic development will have an impact on the supply and demand of economic goods and services that is large relative to the impact of climate change.

(Arent et al. 2014, emphasis added)

That statement is validated by experience. Since 1900, the average global surface temperature anomaly warmed 1.3°C, about as much as the IPCC predicts will occur in the next century under a moderate emissions scenario. But even as the globe warmed and the population quintupled, humanity prospered as never before. For example, global average lifespan went from thirty-two years to seventy-two years, economic activity per capita grew by a factor of seven, and the death rate from extreme weather events plummeted by a factor of fifty!

While extreme weather events are costly, in all modern economies they are becoming steadily less and less important (Formetta and Feyen 2019). Since 1990 weather-related disaster losses have declined as a proportion of global GDP (Pielke Jr 2018, 2020) as have mortality risks (Formetta and Feyen 2019). While economic weather-related insurance payouts are rising, this is fully explained by the growth in the size of the economy and the value of the insured asset stock. Past increases in episodes extreme weather have not had a significant effect (positive or negative) on the market value of insurance firms (Hu and McKittrick 2015). Nor have past extreme weather events had a significant effect on US banks' performance (Blickle et al. 2021).

For these reasons, economists have long been reluctant to endorse attempts to "stop" climate change or even aggressively reduce GHG emissions because the costs would not be worth it. As one critic of the economics of climate policy put it:

Mainstream climate economics takes global warming seriously, but perplexingly concludes that the optimal economic policy is to almost do nothing about it... The contrast is striking. While climate science is sending out loud-and-clear messages that fossil-fuel disinvestment must start now, letting go of coal and oil and diverting resources into renewable energy technology systems, to keep warming below the 2°C limit (IPCC 2014), mainstream climate economics claims that overly ambitious climate targets will unnecessarily hurt the economy and immediate de-carbonization is too expensive. Most climate economists thus recommend humanity to just wait-and-see.
(Storm 2017)

The mainstream economics position on the climate policy question is best represented by the findings over the past three decades from Integrated Assessment Models (IAMs) of climate change policy, for which Yale economist William Nordhaus was awarded the 2018 Nobel Memorial Prize in economics. IAMs combine economic, climate, and social data into a unified framework for simulating climate damages and evaluating the optimal policy response (Resources for the Future 2025). Nordhaus' work has generally supported modest global climate policy, with aggressive measures largely deferred to later in the century. Nordhaus developed the so-called Dynamic Integrated Model of the Climate and Economy model, or DICE, in the early 1990s (Nordhaus 1993) to study the interaction between climate change, climate policy, and global economic growth over long times. DICE assumes global emission control can be coordinated at no cost and asks what the optimal policy target should be. The climate component of the DICE model is based on simplified climatological modeling. The version of DICE at the time of Nordhaus' Nobel Prize award was described in Nordhaus (2018); it had a climate sensitivity parameter of 3.1°C for CO₂ doubling, consistent with the best estimate in contemporary IPCC reports (3.0°C).

The baseline (no policy) scenario incurs only \$0.4T in global abatement costs and leads to \$134.2T (trillion dollars) in global climate damages for a total cost of \$134.6T. The climate model component of DICE projects 4.1°C warming by 2100 relative to preindustrial temperatures. Note that this is a higher estimate of warming than many IPCC climate models. (AR6 offers 2.7°C in 2100 under a moderate emissions scenario.)

The Optimal Policy scenario barely deviates from the business-as-usual path. It aims for +3.5°C warming, in other words we scale back only the lowest-value fossil fuel use and otherwise just live with almost all the warming. This suggests that most CO₂ emissions are less harmful than the policies that would be necessary to abate them. Trying to prevent warming causes costs quickly to outstrip the benefits. Pursuing a goal of capping warming at 2.5°C creates total costs of \$177.8T,

which is \$43.2T worse than doing nothing at all. Nordhaus didn't evaluate trying to reach a Paris-type target of 1.5°C warming but it would be even worse.

A subsequent edition of DICE includes higher assumed damages from warming which, not surprisingly leads to more aggressive policy recommendations, as explained in the section below on the Social Cost of Carbon.

13.1.2 Empirical analysis of climate change and economic growth

Many other studies have used econometric methods instead of IAMs to look at the potential impact of climate change on economic growth. Dell et al. (2012, herein DJ012) was an influential study that used a multi-country panel of national-level data spanning 1950 to 2005, in which they matched climate and economic data by averaging temperature from the local grid cell level up to the national level using population weights. They found that warming yields an insignificant positive effect on income growth in rich countries but a significant negative effect in poor countries. Moore and Diaz (2015) modified the DICE model to take that finding into account and concluded that it implied a dramatically higher Social Cost of Carbon due to the compounding effects of income loss over time.

A large subsequent literature has debated the robustness of the DJ012 findings. Burke et al. (2015) analyzed a global panel with temperatures averaged up to the national level and found a negative effect on growth from warming in rich and poor countries alike when the national average temperature is above 13°C. Zhao et al. (2018) used the G-Econ data set of Nordhaus (2006), which breaks economic activity down to the grid cell level, replicated DJ012-type results on the same subset of countries as used in DJ012 but then showed that on the full global sample warming increases growth in rich countries and poor countries alike, though the positive effect in the latter group is confined to where local temperatures are below about 16°C. Greßer et al. (2021) developed a regional economic data set for 1,542 sub-national regions around the world between 2005 and 2015 and found temperature had no effect on growth. Yang et al. (2023) updated the DJ012 data set and applied an estimator robust to mixed sample frequencies, finding that while temperature shocks exerted a temporary effect on income levels, they did not have a significant lasting effect on growth rates.

Newell et al. (2021) noted that there is no underlying theory to guide econometric model specification in this literature. Taking into account the arbitrary choices of which explanatory variables to include they identified over 800 possible model specifications. Using the Burke et al. (2015) data they used an estimation method that accounts for model uncertainty and found that the model form preferred by Burke et al. (2015), which implied negative effects of warming on growth even in rich countries, is explicitly excluded by the optimal model selection algorithm. Overall they could not detect a temperature effect on GDP or GDP growth, and they estimated the 95% confidence interval for the impact on global growth as of 2100 even under the exaggerated RCP8.5 warming scenario spans -86 percent to +388 percent. In other words the net effect is likely positive but too uncertain to distinguish from zero.

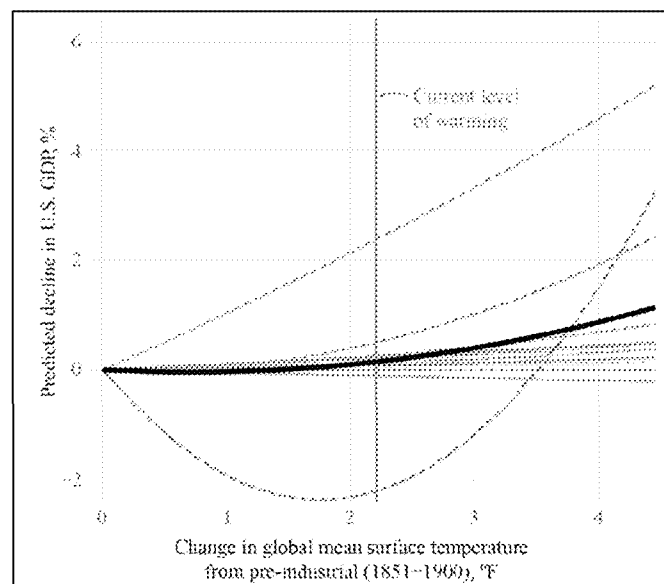
Barker (2023) criticized the DJ012 assumption that countries can be grouped into fixed “poor” and “rich” categories based on their incomes many decades ago. He noted that many countries were once poor but became rich over time, and if this is considered the original temperature effects reported by Dell et al. became small and insignificant.

Berg et al. (2023) argued that countries shouldn't be grouped into large Rich/Poor categories because they are too heterogeneous. They instead estimated country-specific temperature response coefficients then grouped countries with similar response coefficients into small panels. They

separately estimated responses to global and idiosyncratic local temperature shocks to better identify the climate signal in weather data. Overall they found countries experiencing negative effects of warming on growth outnumbered those experiencing positive effects, but only temporarily: eventually the effects reverse such that about twice as many countries experience a net positive growth effect. They also found global (as opposed to local) temperature changes are much more likely to benefit growth in poor countries than rich ones. In a simulation to 2100 even using the extreme RCP8.5 scenario they computed the average global GDP loss would be only 1.9% compared to a scenario with no warming. That is, instead of the economy growing 400% it would grow 398%. The implication of Nordhaus' analysis is that trying to prevent the warming would lead to far less than 398% growth.

To summarize, economists have long considered climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in the Fifth Assessment Report. Mainstream climate economics has recognized that CO₂-induced warming may have some negative economic effects but they are too small to justify aggressive abatement policy, and trying to “stop” or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries but it has subsequently been found not to be robust. Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit from it as rich countries.

The expectation that significant global warming would have a small impact on the U.S. economy was acknowledged quietly by the Biden Administration, even as the President was proclaiming a climate emergency. The following figure, from a 2023 OMB-CEA [report](#), shows the expected decrement in U.S. GDP as a function of temperature rise. The colored lines show the results of a dozen peer-reviewed published studies while the solid black line is their average. The figure could be summarized as “a few percent impact for a few degrees of warming”. Given that the economy’s annual growth rate is expected to be 1-2 percent, the impact of a warming globe is indeed negligible.



13.2 Models of the Social Cost of Carbon

The Social Cost of Carbon (SCC) is a tool for quantifying the economic impact of carbon dioxide emissions, helping policymakers weigh the costs and benefits of climate policies. It estimates the damage caused by emitting one additional ton of CO₂, expressed in dollars. More formally, the SCC is the discounted present value of the current and future marginal loss of economic welfare due to an additional ton of CO₂ entering the atmosphere. On its own the SCC is not the appropriate price to attach to CO₂ emissions for the purpose of optimal emissions control but it can be converted into an optimal tax rate by scaling it by the Marginal Cost of Public Funds (MCPF). The theory behind this was first derived by Sandmo (1975) and has been reiterated many times since then by other economists working on the topic (e.g. Parry et al. 1999). The MCPF is the cost in terms of lost private economic welfare of raising public revenue by one dollar and always exceeds unity. If a jurisdiction does not use a carbon tax, this formula still indicates the upper bound on the amount emitters should spend on abatement options at the margin along the optimal policy path. Regulations should be imposed only insofar as they do not impose marginal abatement costs in excess of the optimal tax rate.

13.1.2 Estimating the SCC

Although the literature refers to “estimates” of the SCC, it is not estimated in the way other economic statistics are estimated. For instance, data on market transactions including prices and quantities can be used to estimate the current inflation rate or the growth rate of per capita real Gross Domestic Product, and there are well-understood uncertainties associated with these quantities. But there are no market data available to measure many if not most of the marginal damages or benefits believed to be associated with CO₂ emissions, so these need to be imputed using economic models.

For example, an influential component of some SCC calculations is the perceived social cost associated with changed risk of future mortality due to extreme weather. There is no market in which people can directly attach a price to that risk. At best economists can try to infer such values by looking at transactions in related markets such as real estate or insurance, but isolating the component of price changes attributable to atmospheric CO₂ levels is very difficult.

Economists use IAMs to compute the SCC. Two of the best known IAMs are the Climate Framework for Uncertainty, Negotiation and Distribution (“FUND”, Tol 1997) and Nordaus’ DICE. IAMs embed a stylized global climate model with a very simplified representation of the global economy, including a “damage function” or set of functions relating ambient temperature to local economic conditions. The assumptions embedded in the damage function will largely determine the resulting SCC.

One approach to developing a damage function is to begin with estimates of the costs (or benefits) of warming in specific sectors in countries around the world and aggregate up to a global amount. This was the approach used in FUND. An alternative approach is to develop a simple equation that penalizes global income according to a simple quadratic function of the average global temperature. This approach was used in DICE. In the case of the FUND model many hundreds of parameters had to be selected, whereas in DICE only three were needed and were originally chosen to assign a predetermined penalty (1.2%) to global output as of 3°C warming, with a quadratic term implying that damages grow with the square of the global average temperature anomaly. Barrage and Nordhaus (2024) recently changed the parameters to increase the penalty at 3°C to 1.6%, and added a discrete additional 1.0% GDP penalty at 3°C warming to account for “tipping points” (discrete large-scale environmental changes triggered by crossing a warming threshold) and a “judgmental adjustment” of 0.5% for excluded impacts at 3°C warming. Not surprisingly the newer version of DICE generates much higher SCC estimates than before.

The concepts of estimation and uncertainty do not readily apply to SCC calculations. By comparison, the question of whether precipitation has trended up or down along the South Carolina coast for the past hundred years can be addressed by collecting rainfall data, estimating a trend parameter and calculating statistical confidence intervals using methods with well-understood mathematical properties. In this way uncertainty can, in principle, be resolved by collecting more data and applying more accurate methods. But no amount of data collection can change the fact that many components of the SCC are unknown and rely on judgment and opinion based on knowledge of the underlying literature on the physical effects of climate change.

SCC calculations are thus best thought of as “if-then” statements: *if* the following assumptions hold, *then* the SCC is \$X per tonne. The list of ‘if’ statements includes the premise that the world’s climate and economy work according to the representation in the IAM. One way this may fail to hold is in the timing of warming. Every IAM assumes a value of the Equilibrium Climate Sensitivity (ECS), controls the amount of warming that results from CO₂ emissions and can be freely varied for the purpose of generating a distribution of SCC values associated with uncertainties over ECS. But as Roe and Baumann (2013) pointed out, time-to-equilibrium increases with the square of ECS, so an upward adjustment of the ECS parameter without an appropriate slowing down of the adjustment process can yield distorted present value damage estimates. In particular, the upper tail of warming associated with some commonly-used ECS distributions is physically impossible for even a thousand years into the future (Roe and Baumann 2013) yet in an IAM would be realized within a couple of centuries. Failure to align ECS with time-to-equilibrium will lead to an overestimate of the SCC value.

13.2.2 Variations in the SCC

Every level of the IAM calculation includes assumptions, some more influential than others. Key assumptions include the following.

- The discount rate: Climate damages accrue over a long time horizon, and costs a century or two in the future need to be discounted to the present. The higher the discount rate the smaller the present value of future damages and vice versa. The discount rate represents the opportunity cost of spending money today rather than investing it and then having more to spend tomorrow. Some economists have argued for the use of very low discount rates in SCC calculations, resulting in policy recommendations that favor relatively large immediate investments in CO₂ emission reductions. The downside is that other investments could potentially earn a larger rate of return for society.
- Equilibrium Climate Sensitivity: IAMs have customarily employed a value of 3.0°C or 3.1°C following the IPCC’s guidance. Empirically-estimated ECS values tend to be lower than this (see Chapter XX). Dayaratna et al. (2017, 2020, 2023) have shown that use of lower empirically-derived ECS values dramatically lower the resulting SCC estimate, even when low discount rates are used.
- Damage function coefficients: IAMs assume CO₂ and warming cause net harms that increase exponentially with temperature. More recently, IAMs have also incorporated effects from assumed potential climate tipping points. The FUND model took limited but explicit account of CO₂ fertilization effects in agriculture. Since the coefficients were selected prior the publication of the current evidence of global greening and the magnitude of benefits to crops from elevated CO₂ (see Chapters 2 and 10) the growth effects are likely understated.

The DICE model (and others) did not explicitly include any CO₂ fertilization benefit, except to the extent it was taken into account in the literature consulted when picking the damage function coefficients. The damage function in FUND contains a region in which low warming yields net benefits in many regions, a finding which is supported by econometric models of warming and growth (Berg et al. 2023) and econometric simulations of agricultural changes (McKittrick 2025). The DICE damage function, by construction, rules out net benefits at any warming level.

- Emission scenarios: IAMs generate SCC estimates that increase as the pre-existing concentration of CO₂ increases. Consequently the value of damages later in the century will be higher, depending on the assumed baseline emissions over the coming decades.
- Abatement costs: IAMs represent the cost to the economy of reducing CO₂ emissions. If CO₂ emission reductions are assumed to be inexpensive, then the model will conclude that the optimal policy should aim for deeper emission cuts and vice versa.

It is informative to ascertain whether SCC results are invariant to changes in some assumptions. But when different assumptions result in higher or lower SCC values, the change in the SCC value does not provide *prima facie* evidence about the validity of the assumptions. For example, in 2023 the US Environmental Protection Agency raised its preferred SCC value about 5-fold over the estimates it had issued ten years earlier. This is not because new data had been collected or better mathematical methods had been invented, but because new assumptions had been used, and the validity of those assumptions was a separate question. One was that global agricultural damages were far higher than previously assumed, based on an analysis in Moore et al. (2017). But as discussed in Section XX, McKittrick (2025) showed that Moore et al. (2017) had used a database in which half the CO₂ change observations were missing. When as many of those observations as possible were recovered from underlying sources and the analysis was rerun, the projected crop yield losses disappeared and turned into gains at all warming levels. Hence the portion of the EPA's SCC revision attributable to agricultural yield losses was unwarranted.

13.2.3 Evidence for low SCC

Chapter 2 reviewed evidence on climate change and greening, and Chapter 10 looked at climate change and US agriculture. Evidence shows that CO₂ fertilization has a stronger beneficial effect on agriculture than was known at the time that IAMs like DICE and FUND were parameterized. In particular Haverd et al. (2020) found the observed CO₂ fertilization rate has been almost double what had been predicted by crop models. Dayaratna et al. (2023) used the updated empirical ECS distribution estimate of Lewis (2022), which assimilates modern instrumental and paleoclimatic temperature records, and allowed for a 30 percent gain in the CO₂ fertilization benefit in the FUND model, and found that, even at a low discount rate of 2.5 percent, the median SCC as of 2050 is only \$18.67, with a 24 percent probability of the true value being negative. At a five percent discount rate the median SCC value is negative until the mid-2040s and at 2050 was only \$0.37 with a 49 percent probability of being negative. Thus, under reasonable assumptions a mainstream IAM using updated scientific inputs yields evidence consistent with the SCC not being significantly greater than zero.

It should also be noted that the SCC is focused on the social costs of CO₂ emissions from fossil fuel use. It does not measure the private marginal benefits to consumers and society from the availability of fossil fuels. Public willingness to pay for fuels of all types indicates the value to society of reliable, abundant fossil energy. Tol (2017) estimates that the private benefit of carbon is

large relative to the social cost. This can be illustrated by noting that the price of a gallon of gas indicates the marginal value to the consumer of the fuel. Suppose we assume a relatively high Social Cost of Carbon of, say, \$75 per tonne. Deflated by a MCPF value of 1.5 that would result in a carbon tax of \$50 per tonne, which equates to about 44 cents per gallon of gas (Lavelle 2019). A pre-tax price of \$3.00 per gallon would imply the marginal social benefit of the fuel is nearly seven times the marginal social cost.

13.3 Summary

It is increasingly being argued that the SCC is too variable to be useful for policymakers. Cambridge Econometrics (Thoung 2017) stated it's "time to kill it" due to uncertainties. The UK and EU no longer use SCC for policy appraisal, opting for "target-consistent" carbon pricing (UK Department for Energy Security and Net Zero 2022, Dunne 2017). However the weaknesses of the SCC concept don't mean that other regulatory measures are inherently better or more efficient. Many climate regulations (such as electric vehicle mandates, renewable energy mandates, energy efficiency regulations and bans on certain types of home appliances) end up costing far more per tonne of abatement than a simple price on carbon emissions.

In summary, SCC estimates are highly uncertain due to unknowns in future economic growth, socioeconomic pathways, discount rates, climate damages, and system responses. The SCC is not intrinsically informative as to the economic or societal impacts of climate change. It provides an index connecting large networks of assumptions about the climate and the economy to a dollar value. Some assumptions yield a high SCC and others yield a low or negative SCC. The evidence for or against the underlying assumptions needs to be established independently; the resulting SCC adds no additional information about the validity of those assumptions.

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U.S. Vehicle-Based CO₂ Emissions and the Global Climate

The EPA's 2009 Endangerment Finding focused on CO₂ emissions from cars and light-duty trucks in the U.S. because Section 202(a) of Clean Air Act mandates the EPA to set emissions standards for motor vehicles if pollutants are found to endanger public health or welfare. Thus, the 2009 Endangerment Finding obligated the EPA to regulate emissions from new motor vehicles.

Two questions that naturally arise are: (1) How large a reduction in CO₂ emissions would result from such regulation? and (2) What would be the climate impact of such regulation?

The first question can be addressed using CO₂ emissions statistics from the EPA and the International Energy Agency (IEA). The second question can be addressed by the fact that the reduction in global warming is proportional to how much global emissions are reduced, keeping in mind that how much the CO₂ content of the atmosphere increases in any given year is the result of total global CO₂ emissions, not just U.S. emissions.

In 2022, the emissions from U.S. cars and light duty trucks totaled 1.03 billion metric tons of carbon dioxide (GtCO₂). This is only 2.8% of the 36.8 GtCO₂ of global energy-related emissions in 2022. If we were to take into account emissions from land use and cement production, that fraction would be even smaller, but for the purpose of the following calculation, it will suffice.

Even if all CO₂ emissions were eliminated from U.S. cars and light duty trucks in 2022, the impact on global warming would be less than 3%. Would such a tiny impact even be measurable in global temperature data? Since we cannot measure decadal temperature trends to this level of accuracy (current temperature trends span a range of 29% across five global temperature datasets)ⁱ, the elimination of all U.S. CO₂ emissions from cars and light duty trucks would have no statistically measurable impact on global warming. Given that global-average temperature is the most robust climate change metric, this means any other climate impacts (e.g. severe weather, floods, drought, etc.) from the elimination of U.S. vehicle CO₂ emissions would be even less significant.

ⁱ For the period 1979-2023, which has the most extensive global coverage of a variety of weather data types, warming trends from five global temperature datasets range from +0.163 deg. C per decade from the NCEP/NCAR R1 reanalysis dataset to +0.211 deg. C per decade for the ERA5 reanalysis dataset. The latter estimate is 29% larger than the former, indicating that a 3% reduction in the rate of global warming from eliminating U.S. vehicle CO₂ emissions would be statistically unmeasurable (monthly reanalysis fields available from KNMI Climate Explorer).

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- 2 The carbon cycle and future emission scenarios
- 3 Aerosols and the uncertainties associated with them

Part II: Climate response to anthropogenic influence

- 4 Measuring climate sensitivity to CO₂ doubling
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Report of the Special Advisory Group on Carbon Dioxide and Climate Change

Submitted to the Secretary, US Department of Energy

May 30, 2025

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Climate Science, Greenhouse Gases
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Foreword: Secretary Chris Wright

Foreword: CSAG

This document originated in late March 2025 when Secretary Wright assembled an independent team to write a report on issues in climate science relevant for energy policymaking, with particular focus on the question of whether carbon dioxide emissions endanger the US public. The team agreed to undertake the work on the condition that there would be no editorial oversight by the Secretary, the Department of Energy, or any other government personnel. This condition has been honored throughout the process and the writing team has worked with full independence.

The team began working in early April with a deadline of May 28. The short timeline and the technical nature of the material meant that we could not comprehensively review all topics. While the report is intended to be accessible for non-experts, we have omitted some introductory or explanatory material that can easily be accessed elsewhere. Nor have we attempted to survey entire literatures related to the topics covered. The scientific and technical material herein only samples vast literature on climate change but is, we believe, more than sufficient to establish our conclusions.

The team writing this report was not involved in, nor briefed on, any Administration plans or processes related to a potential challenge to the 2009 EPA CO₂ Endangerment Finding. We were asked, however, to include some information related to the role of US motor vehicles in global climate change, since that is an issue of relevance to the Department of Energy.

The writing team is grateful to Secretary Wright for the opportunity to prepare this report and for his support for independent scientific inquiry.

Part I: Direct Human Influence on Ecosystems and the Climate

1. Carbon dioxide as distinct from criteria air contaminants

This report is chiefly concerned with carbon dioxide (CO₂) emissions from fossil fuel use. Although it has become common to refer to CO₂ as “pollution” this is a misnomer. In the framework of United States clean air policy there are six types of so-called Criteria Air Contaminants (EPA, undated): particulate matter, ground-level ozone, Sulfur Dioxide, Nitrogen Dioxide, Lead and carbon monoxide (CO). Air contaminants are subject to regulatory control because they cause local problems depending on concentrations that include nuisances (odor, visibility problems), damage to plants and, at high enough exposure levels, toxicological effects in humans.

CO₂ has not historically been viewed as an air pollutant in the US or elsewhere because it is odorless, does not affect visibility and has no toxicological effects at ambient levels. It is a naturally-occurring part of the atmosphere and a key component of human and plant respiration. CO₂ is essential for plant photosynthesis and higher levels are generally considered beneficial for vegetation, as will be discussed in this report.

Ambient outdoor air contains about 420 parts per million (ppm) CO₂. The US Occupational Safety and Health Administration issues guidelines for indoor workplaces in which elevated CO₂ may be encountered, such as where dry ice is used. The Permissible Exposure Limit is 5,000 ppm over 8 hours (OSHA 2024). Allen et al. (2015) reported evidence of diminished performance on some cognitive tasks among workers in office cubicles when exposed to CO₂ levels above 1,000-1,500 ppm.

The main concern about CO₂ is its potential effects on the global climate. This is a very complex question which will occupy much of this report. We will begin in the next section by looking at the role of CO₂ in promoting global greening and agricultural productivity growth, then we will examine the effect of CO₂ on ocean alkalinity. We then turn to CO₂'s role as a so-called greenhouse gas (GHG), beginning with a brief description of radiative forcing, the carbon cycle and the role of aerosols. Part II of this report discusses in detail the topic of the climatic response to GHGs. Part III discusses some aspects of the impacts of climate change on ecosystems and society.

US Environmental Protection Agency (Undated) Criteria Air Pollutants. <https://www.epa.gov/criteria-air-pollutants> accessed April 29 2025.

US Occupational Health and Safety Administration (2024) “OSHA Occupational Chemical Database: Carbon Dioxide” <https://www.osha.gov/chemicaldata/183>

Allen, Joseph G, Piers MacNaughton, Usha Satish, Suresh Santanam, Jose Vallarino and John D.S. Spengler (2015) Associations of Cognitive Function Scores with Carbon Dioxide, Ventilation, and Volatile Organic Compound Exposures in Office Workers: A Controlled Exposure Study of Green and Conventional

2. CO₂ fertilization and global greening

2.1. CO₂ and global greening

“Greening” refers to an increase in the total amount of the Earth’s surface covered in plants. The main measure of greening is “Leaf Area Index” or LAI as measured by satellite. Many studies over the past decade have confirmed a global greening pattern (rising LAI) attributable to rising CO₂ levels. Zhu et al. (2016) was one of the first studies to report that global greening was detectable from space using satellite sensors. On data spanning 1982 to 2011 they detected greening over 25-50% of the Earth versus browning over only 4%, and they attributed 70% of the greening to rising CO₂ levels (see Figure 2.3).

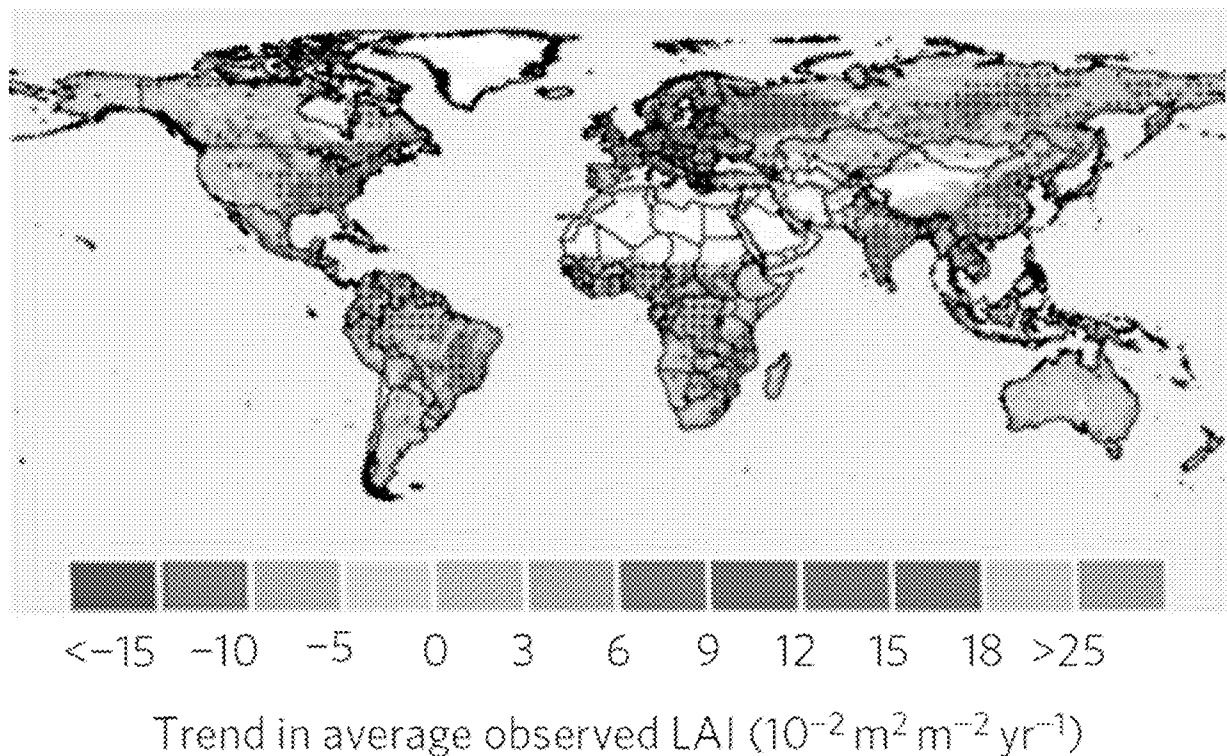


Figure 2.1.1: Trends in average Leaf Area Index (LAI). Source: Zhu et al. 2016 Figure 3.

Zheng (2017) confirmed the pattern, noting that greening over 30 years had added 8% to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen et al. (2019) noted that China and India were taking particular advantage of it though land management changes.

Thus while China accounts for only 6.6% of global vegetated area it accounts for 25% of global net increase in LAI. Piao et al. (2020) noted that greening was even observable in the Arctic.

While plant models predict increases in photosynthesis should be observed in response to rising CO₂, Haverd et al. (2020) reported that observed CO₂ fertilization rate was nearly double what models had predicted. That is, CO₂ fertilization had driven an increase in observed global photosynthesis by 30% since 1900, versus 17% predicted by plant models. Among other things this indicates that global models of the socioeconomic impacts of climate change have likely understated the benefits to crops and agriculture from rising CO₂. The connection between CO₂ fertilization and climate policy will be discussed in Chapter XX.

Finally, Chen et al. surveyed claims that greening had slowed down since 2000 due to drought stress. They found instead that claims of slowed greening could be attributed to faulty satellite sensors. Once the data were corrected they found greening was accelerating over 55% of the world while browning was accelerating over only 7% of the world. Overall the greening trend was continuing with no evidence of slowdown, and CO₂ fertilization remained the dominant driver

2.2. Photosynthesis and CO₂ levels

A key direct effect of adding CO₂ to the atmosphere is its positive effect on plant life via enhancement of photosynthesis and improvement to plant water use efficiency.

The term *photosynthesis* describes the process by which plants build biomass. The process requires carbon dioxide (CO₂), water (H₂O), and light. The plant enzyme responsible for photosynthesis is called Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO₂ is available at the surface of the RuBisCo enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass, which is referred to as the C3 process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth’s atmospheric CO₂ levels were usually much higher than they are today. About 400 million years ago CO₂ levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Berner 2006, Judd et al. 2024). Over the past 35 million years the level of atmospheric CO₂ has been steadily declining. During glaciations levels have fallen as low as 170 ppm (Gerhart and Ward 2010). In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C4, in which CO₂ is concentrated in the vicinity of Rubisco allowing for the C3 process to function more efficiently. For agricultural purposes the plant categories are:

- C3: rice, wheat, soybeans and most other crops
- C4: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth rates would have declined and eventually ceased. Below 180 ppm many C3 species experience growth rate reductions on the order of 40-60% compared to their growth rates at 350 ppm (Gerhart and Ward 2010). C3 plants have been observed under experimental conditions to stop growing altogether at levels between 60—140 ppm CO₂. Some C4 plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Currently, CO₂ levels are about 420 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 1 which is reproduced from Gerhart and Ward (2010). It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains exhibited from increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

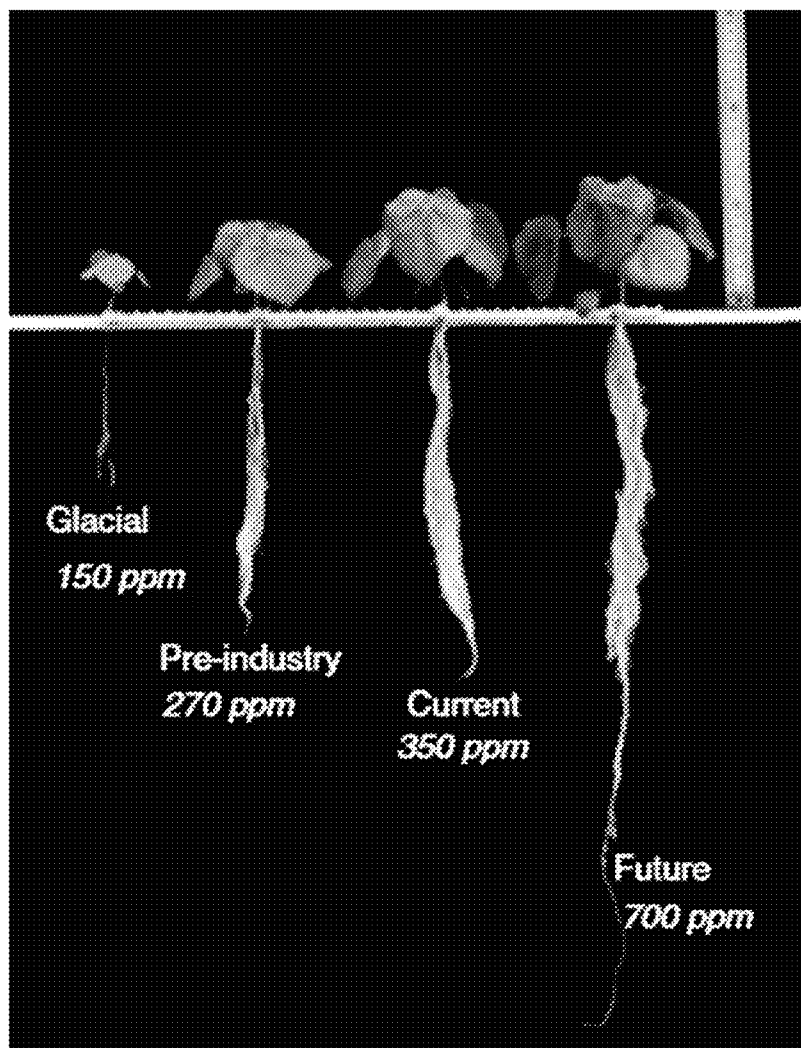


Figure 2.2.1: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010).

Over the past 60+ years there have been tens of thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C3 plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, which allows water to evaporate away. Under enriched CO₂ conditions the stomata are closed for longer periods helping the plant retain water longer, thereby increasing water use efficiency.

Specific effects of climate change on US agriculture will be reviewed in Chapter XX.

2.3. Rising CO₂ and crop water use efficiency

Deryng et al. (2016) surveyed evidence on crop water productivity (CWP), i.e. yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them and once it was taken into account all regions showed a net CWP gain. Deryng et al (2016) also reported that negative impacts of warming on wheat and soybean yields were fully offset by CWP gains, and mitigated by up to 90% for rice and 60% for maize.

Similar to this, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

2.4. Concealment of CO₂ fertilization benefits in IPCC Reports

If CO₂ emissions were discovered to be causing global crop declines and regional browning we would almost certainly have seen it discussed prominently in IPCC reports, and indeed it likely would have been the subject of its own chapter in an Assessment Report if not an IPCC Special Report. By contrast the IPCC has been almost silent on the topic of global greening.

The topic is briefly acknowledged in a few places in the body of the IPCC 6th and earlier Assessment Reports but is omitted in all Summary documents. Section 2.3.4.3.3 of the AR6 Working Group I report is titled “global greening and browning.” It points out that the IPCC Special Report on Climate Change and Land had concluded with high confidence that greening had increased globally over the past 2-3 decades. It then discusses the various estimate of greening trends, notes that there are variations in the estimates among data sets and then says that while they have *high confidence* greening has occurred, they have *low confidence* in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports.

Overall, however, the Policymaker Summaries, Technical Summaries and Synthesis Reports are conspicuous for their failure to discuss the topic.

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3. Increasing CO₂ and the Alkaline Oceans

The modern-day global average pH of sea water is estimated to be 8.1, down from an estimated value of 8.2 in pre-Industrial times (Gattuso and Hansson, 2011). As CO₂ concentrations in the atmosphere increase, more is absorbed by the oceans. Depending upon the alkalinity (buffering capacity) of the oceans, the oceans are expected to become somewhat less alkaline over time, putatively explaining the decrease in pH from 8.2 to 8.1 over the last few hundred years.

While this process is often called “ocean acidification”, this is a misnomer because the oceans are not expected to become acidic (pH less than 7.0). Even if that was to happen, it is believed that life in the oceans evolved during a period when the oceans were mildly acidic, with a pH of 6.5 to 7.0 (Krissansen-Totton et al., 2018).

For many years it was assumed that a decreasing pH of sea water would reduce the calcification rate of coral reefs. But coral reefs already endure large swings in pH, partly due to daily photosynthetic activity in the reef. This results in pH values that have been measured to range from 9.4 during the day to 7.5 at night (Revelle and Fairbridge, 1957).

In 2009 it was reported that a portion of Australia’s Great Barrier Reef (GBR, the world’s largest coral reef ecosystem) had experienced a 14% decline in calcification since 1990 (De’ath et al., 2009). This was tentatively attributed to increasing water temperature and decreasing pH of seawater. But since that time, the initial 2009 report of reduced calcification rates in the GBR was reported to have been the result of a bias in the data analysis (Ridd et al., 2013), and correction for this bias led to no change in calculated calcification rates. Nevertheless, the alarm produced by the original paper has persisted as evidenced by the large number of published citations (541) received by the original study as compared to only 11 citations for the subsequent study (as of 30 April 2025).

Given the reported declines in GBR coverage between 1990 and 2009, it has come as a surprise that the decline reversed over the last decade or so, with Woods Hole Oceanographic Institution asking, “Is the Great Barrier Reef Making a Comeback?” (Woods Hole, 2023). The most recent annual summary of GBR conditions from the Australian Institute of Marine Science was titled, Continued Coral Recovery Leads to 36-year Highs across Two-Thirds of the Great Barrier Reef (AIMS, 2022). Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden et al., 2015), and recovery of the reef from storm damage takes years.

On the time scale of thousands of years, boron isotope proxy measurements of pH show that ocean pH was around 7.4 or 7.5 during the last Ice Age (up to about 20,000 years ago) increasing to present-day values when the world warmed during deglaciation (Rae et al., 2018). Thus, there appears to be considerable resilience of ocean biota to natural long-term changes in ocean pH since marine organisms are exposed to wide ranges in pH anyway.

It is being increasingly recognized that publication bias (alarming ocean acidification results preferred by high-impact research publications) leads to exaggerated impacts from more alkaline oceans. An ICES Journal of Marine Science Special Issue addressed this problem with an article entitled, Towards a Broader Perspective on Ocean Acidification Research. In the Introduction to that Special Issue, H. I. Browman stated, “As is true across all of science, studies that report no effect of ocean acidification are typically more difficult to publish.” (Browman, 2016)

Similarly, a meta-analysis of the negative effects of ocean acidification on reef fishes found that initially dramatic conclusions published in the scientific literature were all but refuted upon subsequent analysis involving larger sample sizes of data (Clements et al., 2021).

In conclusion, it is becoming increasingly apparent that the effect of ocean “acidification” on marine biota has likely been exaggerated.

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4. Human influences on the climate

4.1. Components of radiative forcing and their history

Historical radiative forcing

A changing climate has been the norm throughout the Earth's 4.6-billion-year history. The Earth's temperature and weather patterns change naturally over timescales ranging from decades to millions of years. Natural variations in the surface climate originate in two ways. Internal climate fluctuations associated with circulations in the atmosphere and ocean produce exchanges of energy, water, and carbon between the atmosphere, oceans, land, and ice. External influences on the climate system include variations in the energy received from the sun and the effects of volcanic eruptions. Human activities influence climate through changing land use and land cover. Humans are also changing the composition of the atmosphere by increasing emissions of CO₂ and other greenhouse gases and by altering the concentrations of aerosol particles in the atmosphere.

The earth is warmed by the sunlight it absorbs and cooled by the radiative heat it emits to outer space. Averaged over Earth, each of these processes involve power flows of about 240 Watts per square meter (W/m²). When they are in balance, there are no net external causes of warming or cooling. Human (and some natural) influences on the climate alter this balance and so cause the climate to change.

Influences on the energy balance are quantified by "radiative forcing", the extent to which they disturb the warming/cooling balance; a positive forcing warms while a negative forcing cools. The IPCC's estimated history of major components of radiative forcing since 1750 is shown in the following two figures from the IPCC AR6.

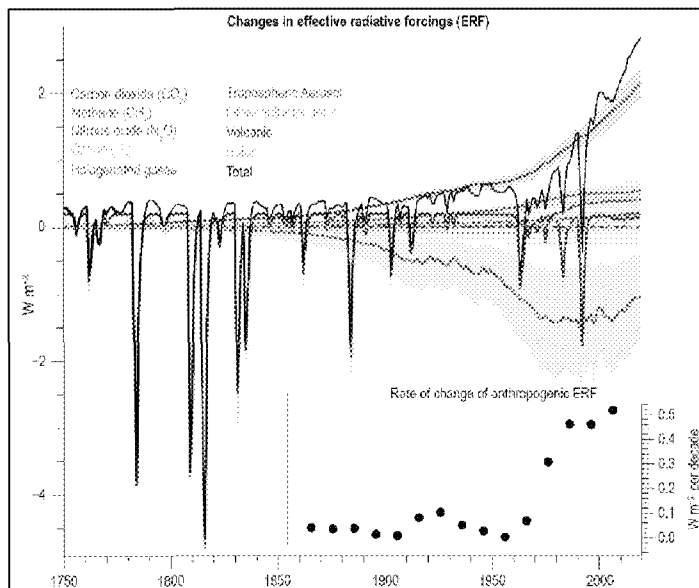


Figure 4.1.1: IPCC estimates of radiative forcing components over time. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-2/figure-2-10/>

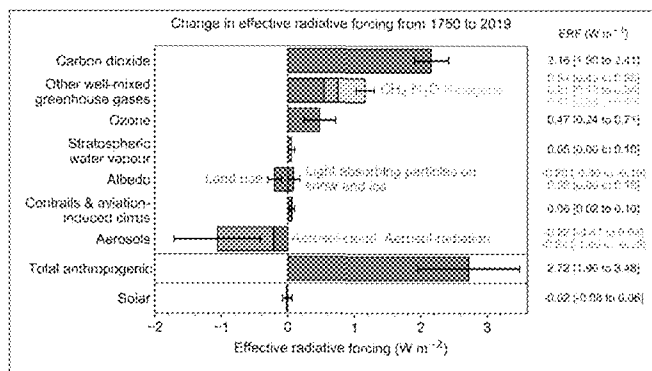


Figure 4.1.2 IPCC estimates of radiative forcing component changes from 1750 to 2019. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-7/figure-7-6/>

These graphs show that the total radiative forcing is comprised of natural and anthropogenic components. Carbon dioxide is the largest human influence on the climate and the one most relevant to the effects of energy-using systems like motor vehicles. It exerts a warming influence by decreasing the cooling power of the atmosphere. Emissions of CO₂ are accumulating in the atmosphere, as described in the following section, so that the warming influence is increasing. Other greenhouse gases (methane, nitrous oxide, halogens, and ozone), which act similarly, currently add another 75% to CO₂'s warming. Aerosols exert a cooling effect, although with large uncertainties in the way they catalyze the formation of reflective clouds. As a result, understanding of the causes of recent warming requires not just identifying the warming effects of CO₂, but also the more uncertain cooling effects of sulfate aerosols.

The IPCC views the role of the sun as negligible, based on their preference for reconstructions that imply minimal solar change since preindustrial times. Connolly *et al.* (2021) reviewed sixteen different Total Solar Irradiance (TSI) reconstructions in the literature covering the 1600-2000 interval; they vary from almost no change in TSI to a relatively large upward trend. Connolly *et al.* point out that the variation in TSI reconstructions combined with variations in surface temperature reconstructions implies pairings can be found that are consistent with either no or most 20th century warming being attributable to the sun. A particularly thorny issue is the gap in the TSI data between 1989 and 1991 due to a delay in the launch of a monitor after the Space Shuttle Challenger disaster on January 28 1986, which prevented a replacement satellite from being launched in time to overlap with, and its readings to be intercalibrated with, the prior system (Zacharias 2014, Scafetta et al. 2019). The question of whether there is an upward trend in TSI over 1978 to 2018 comes down to how the missing data in that gap are filled.

The other natural forcing component is largely volcanic aerosols, which exert an episodic cooling influence.

The anthropogenic forcing component was negligible before about 1900 and has increased steadily since, rising to almost 3 W/m² today. However, this is still only about 1 percent of the unperturbed radiation flows, making it a challenge to isolate the effects of anthropogenic forcing since state-of-the-art satellite estimates of global radiative energy flows are only accurate to a few W/m². Natural sources of

global energy imbalance other than volcanoes are not included in these graphs because they remain largely unknown.

Future radiative forcing

Carbon dioxide's warming influence depends upon how much "extra" CO₂ accumulates in the atmosphere- i.e., its concentration. The CO₂ level as recorded at the Mauna Loa observatory in Hawaii is generally used as the representative global average concentration. The data are available online at <https://gml.noaa.gov/ccgg/trends/index.html>. The concentration was about 316 ppm at the start of the record in 1959 and is now about 425 ppm, a 34 percent increase.

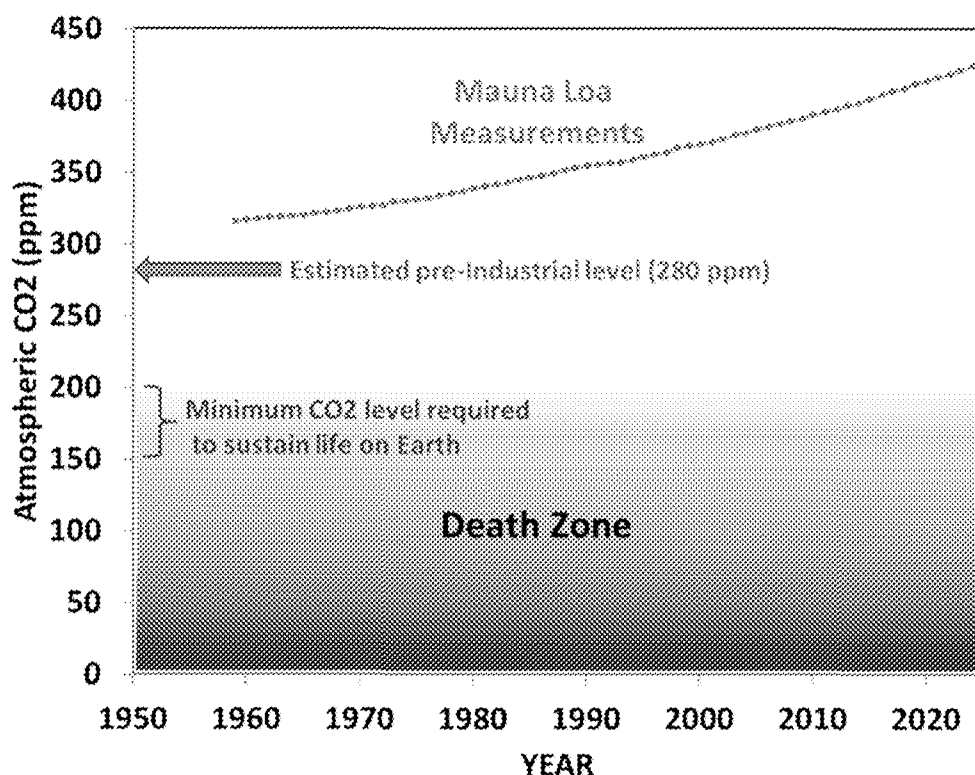


Fig. 4.1.3 Yearly average atmospheric CO₂ concentrations (1959-2024) measured at Mauna Loa, HI (green) compared to the estimated pre-Industrial CO₂ concentration of 280 ppm, and the estimated minimum levels required to sustain life on Earth (150 to 200 ppm). Need source

The annual increase in concentration is only about half of the CO₂ emitted because land and ocean processes absorb "excess" CO₂ at a rate approximately 50% of human emissions. Thus, future concentrations, and hence future human influences on the climate, depend upon two components: (1) future rates of global human CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere. We discuss each of these in turn.

4.2. Future emission scenarios and the carbon cycle

Emission scenarios

Assessing the future dangers of GHG emissions requires assumptions about what those emissions will be. Future emissions, and hence human influences on the climate, will depend upon future demographics, economic progress, regulation, and the energy and agricultural technologies in use. Various assumptions about each of those lead to projections of greenhouse gas emissions and concentrations, aerosol concentrations, and changes in land use, which ultimately can be combined into assumptions about anthropogenic radiative forcing.

Because of the great uncertainties about these many factors in the decades to come, instead of making precise predictions of future concentrations, the IPCC has created various sets of scenarios meant to span a plausible range of possibilities for population, economy, technology, and so on. Recent versions of the scenarios are labeled by a number indicating the anthropogenic radiative forcing expected in 2100 under that scenario. Thus, a scenario labeled with a “6” corresponds to 6 W/m² of human-induced radiative forcing (warming) at the end of the century. (Recall current anthropogenic radiative forcing is about 2.7 W/m².)

Although the IPCC does not put its emission scenarios forward as forecasts they are often treated as such. Comparisons of past scenario groups against observations shows a tendency for IPCC emission projections to overstate actual subsequent emissions. For the IPCC Third and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* were used and hence were referred to as the SREP scenarios. McKittrick *et al.* (2012) showed that, when converted to per capita terms, the SREP scenario distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by the later analysis in Hausfather *et al.* (2019) who showed that observed atmospheric CO₂ concentrations tracked the low end of the SRES range.

For the Fifth Assessment Report the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCP). These were identified by a number representing the increase in forcing and were thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying a radiative forcing in 2100 of 2.6 W/m²) projects a GHG concentration pathway leading to warming well below 2 C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5 C warming just in this century.

RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario in both the academic literature and popular media. It was therefore used to generate the reference outcome supposedly representing the 21st century world in the absence of emission reduction policies. But RCP8.5 was intended as a low-probability high emissions scenario and its usage as a business-as-usual baseline has been criticized as grossly misleading.¹ Hausfather and Peters (2020) writing in a commentary in *Nature* magazine, pointed out that RCP8.5 was developed as an extreme worst-case, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting:

¹ This extreme scenario is useful for modelers, since a large forcing generates a large response (warming) making it easier to assess a model’s sensitivity. But that’s very different than claiming it is a plausible future.

RCP8.5 was intended to explore an unlikely high-risk future. But it has been widely used by some experts, policymakers and the media as something else entirely: as a likely ‘business as usual’ outcome. A sizeable portion of the literature on climate impacts refers to RCP8.5 as business as usual, implying that it is probable in the absence of stringent climate mitigation. The media then often amplifies this message, sometimes without communicating the nuances. This results in further confusion regarding probable emissions outcomes, because many climate researchers are not familiar with the details of these scenarios in the energy-modelling literature. (Hausfather and Peters 2020)

The implausibility of the RCP8.5 scenario was examined by Burgess *et al.* (2021). They noted that RCP8.5 has already diverged from observed energy use trends, and the near future trends diverge sharply from those of the International Energy Agency (IEA) which provides market-based projections of energy use for coming decades. IEA trends are based on plausible extrapolations of current economic and demographic trends, and the results run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but even lower emission scenarios are looking unlikely. Burgess *et al.* comment (p. 8):

Beyond 2040, if the trends anticipated by energy agency forecasts continue, carbon intensity will continue diverging from AR5 and SSP baselines—especially from higher-emission scenarios such as RCP8.5, due to the assumptions about fossil-fuel expansion in these scenarios that are increasingly implausible.

Widespread use of RCP8.5 has created an alarmist bias in the climate impacts literature. The extent of this problem was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found (p. 32) that some 16,800 scientific papers published between 2010 and 2020 used the RCP8.5 scenario, with about 4,500 of the articles (p. 16) linking RCP8.5 with the concept of “business-as-usual”. Their analysis showed how RCP8.5 was misused not only by individual researchers, but also by influential science agencies like the IPCC and the US National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets. They offer the following example (p. 30):

The USNCA employed RCP8.5 as a baseline scenario, despite warning against such use, and compared it to RCP4.5 throughout its report to generate quantitative economic estimates of the benefits of mitigation. In a front-page story, the *New York Times* promoted the report’s misuse of RCP8.5 as a baseline scenario:

“A major scientific report issued by 13 federal agencies on Friday presents the starkest warnings to date of the consequences of climate change for the United States, predicting that if significant steps are not taken to rein in global warming, the damage will knock as much as 10 percent off the size of the American economy by century’s end.”

Pielke and Ritchie (2020) reported new studies using RCP8.5 were appearing in the literature at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and “business as usual.” They conclude (p. 34) that the climate research community has spent a decade “committing scientific resources to science fiction” (emphasis added):

“Derived estimates from RCP8.5 as “business as usual” such as future climate impacts, the impacts avoided from mitigation and the cost effectiveness and benefits of mitigation have no real-world meaning... **The scientific literature has become imbalanced in an apocalyptic direction.**

(Pielke Jr. and Ritchie p. 34)

The IPCC later converted the RCP scenarios to the “Shared Socioeconomic Pathway” or SSP scenarios, but these have continued the pattern of bias shown with the RCP and SRES scenarios. Figure 3.1.4 was generated using the Resources for the Future Global Energy Outlook tool (RFF 2025). The black line shows total global observed CO₂ emissions compiled by the International Energy Agency (IEA). The solid green line is the emission trajectory developed by BP Energy taking account of current emission control policies and global energy use outlooks. It overlaps a solid black line which represents the emission projection from the IEA also taking account of energy use projections and current policies. The dashed lines show the range of IPCC SSP policies. As of 2023 global CO₂ emissions have been tracking well below the SSP scenarios especially the two highest ones (SSP5-8.5 and SSP3-7.0).

Carbon dioxide emissions (Million metric tons), by Outlooks & Scenarios. Filtered by Region: World; Fuel: All; Outlook: 2023 Shell (Sky 2050).

Source: RFF Global Energy Outlook at www.rff.org/gpo

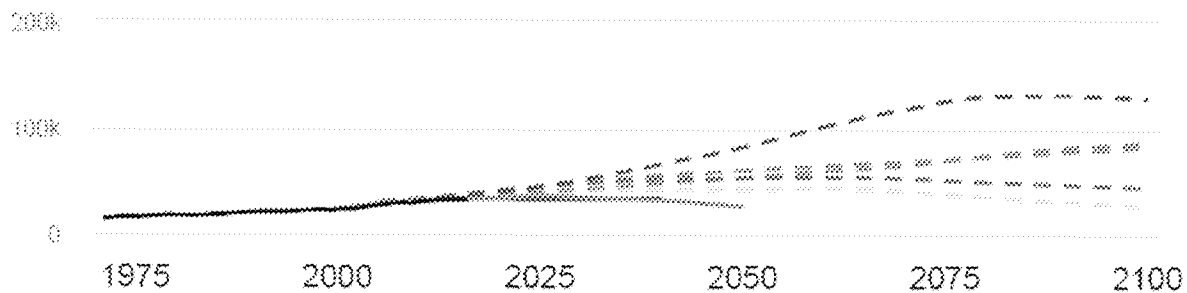


Figure 4.2.1. Observed and projected CO₂ emissions. Source: RFF (2025).

The carbon cycle relating emissions and concentrations

Global carbon cycle models relate concentrations to emissions using estimates of various land and ocean processes that remove CO₂ from, and emit CO₂ into, the atmosphere. Our understanding of these processes was reviewed by Crisp et al. (2021). The natural fluxes of CO₂ in and out of the Earth’s surface are very large, many times anthropogenic emissions, but those CO₂ sources and sinks were assumed to be in approximate balance in pre-Industrial times, as evidenced by relatively constant levels of

atmospheric CO₂ in centuries past derived from air bubbles in ice cores. This is one of several reasons why increasing atmospheric CO₂ levels are believed to be dominated by anthropogenic sources.

Specifically, fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) has led to steadily increasing CO₂ levels in the atmosphere, as shown in Fig. 1.2.1. CO₂ emissions from fossil fuel burning is a small fraction of the natural carbon cycle components. About 44,000 Gigatonnes of carbon-equivalent (GtC) are stored in the atmosphere and oceans, mostly in the form of CO₂. (Ciais et al. 2013). Between 150 and 200 GtC are released naturally each year through oceanic outgassing and land-based processes like plant decay and animal respiration. A variable but roughly equivalent amount is absorbed each year by the land and oceans, with a small net loss from the atmosphere because the formation of deep ocean sediment sequesters some carbon permanently. Global fossil fuel consumption and cement manufacture released about 10.3 GtC in 2023, up from 6.2 GtC in 1990 (Ritchie et al. 2024). Of this, about half is naturally sequestered through plant growth and oceanic uptake while the remainder, about half, adds to the atmospheric stock (Ciais et al. 2013).

As noted, each year natural processes remove a net amount of CO₂ equivalent to about 50% of global emissions. Thus, anthropogenic CO₂ emissions average twice what is required to explain the atmospheric rise in CO₂ concentration. The near-constancy of that 50% fraction (the “airborne fraction”) also means that the more CO₂ humanity produces, the faster nature removes it from the atmosphere. That 50% fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Nino, La Nina, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert et al., 2004).

The main processes which remove excess CO₂ from the atmosphere are increased production of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein et al., 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon observed by satellites since monitoring of global greenness began in the 1982. This greening has been traced to CO₂ fertilization and greater drought tolerance of plants exposed to elevated CO₂ levels. While there had been some uncertainty whether a greening trend continued beyond 2000, the most recent research (Chen et al., 2023) has shown continued greening, with even some slight acceleration since 2000. Global greening is discussed further in Section 3.1.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be reliably measured. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp et al. (2021).

Public policy can only change the rate of emissions, not the concentration in the atmosphere. For criteria air contaminants the rate and concentration are closely connected because the lifetime is short and the concentration is small. When emissions are reduced the local pollution concentration drops rapidly, usually on a time scale of a few days. Not so with the global average CO₂ concentration since global carbon cycle is vast and slow. A change in local emissions today will only have a very small global effect, and only after a long time lag. After a pulse (release) of CO₂ emissions to the atmosphere only about 40 percent ($\pm 15\%$) of the extra CO₂ will have been sequestered after twenty years. After a

thousand years about 75 percent ($\pm 10\%$) will have been sequestered, and the remainder will gradually be removed over the ensuing tens of thousands of years (Ciais et al. 2013, pp. 472-473). Consequently US CO₂ emission reductions will take decades or centuries to lead to a reduction in the global CO₂ concentration.

To reduce the atmospheric stock of CO₂, assuming the entire increase is anthropogenic, would require emissions to fall below the natural sequestration rate. Since that rate has been averaging about 50% of emissions, a reduction of global emissions by 50% would (at least temporarily) halt the rise in atmospheric CO₂. The 1997 Kyoto Protocol proposed to cap industrial nations' CO₂ emissions at a modest five percent below 1990 levels by the year 2012. Even though this policy ended up too costly for most nations to implement, full compliance would not have substantially reduced atmospheric CO₂ levels. It would only have slightly slowed CO₂ growth, reaching the projected 2100 level in 2105 instead (Wigley 1998). Similarly, Lomborg (2016) used the widely-used MAGICC climate model and showed that full compliance with the Paris Accord would not stop warming, it would only prevent about 0.1C warming and delay hitting the baseline year 2100 temperature levels by about a decade.

Thus, in contrast with conventional air pollution control, local actions yield extremely small local effects, and only after a long time lag. The practice of referring to unilateral US reductions as “combatting climate change” or “taking action on climate” reflects a profound misunderstanding of the scale of the issue. As will be discussed in Chapter 14, the scale problem is compounded by recognizing that US motor vehicles account only for about 4 percent of global CO₂ emissions so even a fifty percent reduction in those emissions would have a vanishingly small effect on the global climate.

4.3. Aerosols and the uncertainties associated with them

The climate's sensitivity to CO₂ (as quantified by ECS, the Equilibrium Climate Sensitivity²) is uncertain because the net forcing results from (at least) two counteracting components: warming from GHG's and cooling from aerosols. The observed warming can therefore be made to be consistent with a wide range of pairs of these forces. In the following schematic, the net warming represented by the red arrow could be due to the High GHG warming/strong aerosol cooling pair, or the Low GHG warming/weak aerosol cooling pair, or something in between.

² ECS is formally defined as the increase in equilibrium global average surface temperature resulting from a doubling of the atmospheric CO₂ concentration above its pre-industrial value of 280 ppm. Estimates of ECS are reviewed in Section XX.

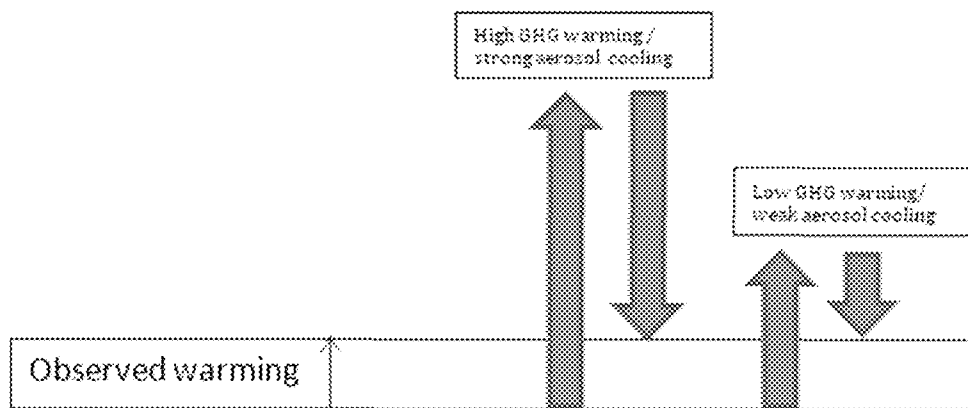


Figure 4.3.1: High and low climate sensitivity to GHGs can be reconciled with the same warming by assuming an offsetting aerosol cooling effect.

Research on the strength of aerosol cooling is therefore central to more precise ECS estimates. Lewis and Curry (2018) note that after the IPCC AR5 was published in 2013, eleven studies appeared in the scientific literature all finding that aerosol cooling was weaker than had previously been conjectured. Combining the updated aerosol estimates with greenhouse gas, ocean heat uptake and atmospheric warming data from the IPCC and applying standard empirical methods, Lewis and Curry (2018) estimated the best-guess ECS to be 1.66°C with a 95 percent uncertainty range of 1.15 °C – 2.7°C. They concluded that based on the ECS values derived from most IPCC climate models were incompatible with observed data.

There has been further evidence of lower aerosol cooling (implying lower ECS) such as Liu et al. (2021). These authors tested the hypothesis that aerosols from wildfires has increased since before the 20th century which, if true, would mean there had to have been relatively strong CO₂ warming over that period offsetting the aerosol cooling. They examined soot layers in ice cores extracted from Antarctica and South America and determined that wildfire activity prior to the 20th century was higher than previously believed. Instead of wildfire activity rising steadily from the 1700s to the present, it was high all the time, thus contradicting the hypothesized aerosol cooling trend in the Southern Hemisphere during the 20th century. They pointed out how this finding relates to the climate sensitivity issue:

Accurate estimates of aerosol radiative forcing are also crucial for better understanding the transient climate response (TCR) and equilibrium climate sensitivity (ECS) to increasing CO₂ and more accurate projection of future climate change. The negative aerosol radiative forcing can, in part, cancel out the positive forcing of increasing greenhouse gases and contribute to the uncertainty of total radiative forcing. An overly large aerosol cooling implies that models might overestimate TCR and ECS to reproduce historical temperature response. A recent study using one of the latest-generation CMIP6 climate models (E3SM) suggested that reducing both the magnitudes of negative aerosol radiative forcing and climate sensitivity yields a better agreement with the observed historical record of the surface temperature.

(Liu et al. 2021)

More evidence pointing to weak aerosol cooling was reported by Wang *et al.* (2021). They noted that the strength of aerosol cooling is partly mediated by cloud behavior and differs between the North and South Hemispheres because of the different density of aerosol emissions. This allowed them to construct another test of climate model validity, which came out in favor of low ECS models. In their words:

Since anthropogenic aerosols primarily concentrate in the Northern Hemisphere, strong aerosol-cloud interaction models produce an interhemispheric asymmetric warming. We show that the observed warming asymmetry during the mid to late 20th century is more consistent with low ECS (weak aerosol indirect effect) models.

Wang et al. (2021)

To summarize, quantifying warming due to CO₂ requires understanding the strength of aerosol cooling. While that latter is uncertain a substantial body of recent evidence points to it being relatively weak, implying that CO₂ warming is likewise weak.

Summary

- The global climate is naturally variable. Anthropogenic CO₂ emissions add to that variability by changing the total radiative balance in the atmosphere.
- The IPCC has downplayed the role of the sun in climate change but there are Total Solar Irradiance reconstructions that imply it might have been important, and the modern record is uncertain due to an interruption in satellite coverage.
- Projections of anthropogenic emissions are combined with carbon cycle model estimates of atmospheric CO₂ removal to estimate future CO₂ concentrations and hence the radiative forcings. These are input to climate models to estimate future anthropogenic changes in the climate.
- IPCC emission scenarios envelopes have tended to exceed observed trends.
- The vast majority of academic climate “impacts” studies in recent years are based upon the extreme RCP8.5 scenario that is considered implausible; its usage as a business-as-usual scenario is misleading.
- Despite ample evidence that scenario envelopes are exaggerated, and despite criticism of this practice in the peer-reviewed literature, the IPCC’s most recent scenario set (SSP) perpetuates this malpractice.
- The global carbon cycle heavily dampens the effect of changes in local (e.g. U.S.) CO₂ emissions. Even global-scale emission reductions will have only small, much delayed effects.
- Knowing the magnitude of CO₂ warming requires knowing the strength of aerosol cooling. While that is uncertain, a substantial body of recent evidence points to it being relatively weak, implying CO₂ warming is likewise weak.

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Zacharias, Pia (2014) An Independent Review of Existing Total Solar Irradiance Records. *Surveys in Geophysics* 35 pp. 897—912 <https://link.springer.com/article/10.1007/s10712-014-9294-y>

Liu, Pengfei et al. (2021) “Improved estimates of preindustrial biomass burning reduce the magnitude of aerosol climate forcing in the Southern Hemisphere” *Science Advances* 7(22) May 2021 <https://doi.org/10.1126/sciadv.abc1379>

Wang, C., Soden, B. J., Yang, W., & Vecchi, G. A. (2021). Compensation between cloud feedback and aerosol-cloud interaction in CMIP6 models. *Geophysical Research Letters*, 48, e2020GL091024. <https://doi.org/10.1029/2020GL091024>

Part II: Climate Response to Greenhouse Gas Emissions

5. Climate Sensitivity to CO₂ Forcing

5.1. Introduction

The sensitivity of Earth's climate to increasing concentrations of CO₂ is at the heart of the scientific debate on anthropogenic climate change, and also the public debate on the appropriate policy response to increasing CO₂ in the atmosphere. Equilibrium Climate Sensitivity (ECS) refers to the expected amount of warming averaged over the Earth's surface in response to a doubling of CO₂, after all climate systems have had time to adjust. Some systems, like temperatures in the troposphere, adjust very rapidly, whereas others such as the deep ocean and ice sheets may take decades or even centuries. A related metric which is helpful for analysis on shorter time scales is the Transient Climate Response (TCR), defined as the amount of warming after 70 years in which atmospheric CO₂ increases by one percent annually.

In 1979 the Charney (1979) Report for the US National Academy of Sciences proposed that the most likely value for ECS was 3.0°C plus or minus 1.5°C. The ECS range between 1.5 and 4.5°C is characterized by the IPCC AR5 as the likely range (66 percent probability); the AR5 stated that ECS is extremely unlikely (95 percent probability) to be below 1.0°C and very unlikely (90 percent probability) to exceed 6.5°C. This range of ECS values has remained stubbornly wide, despite many individual studies claiming to narrow it. Most recently, the IPCC AR6 narrowed its assessment of the likely range of ECS to 2.5–4.0°C and the very likely range to be between 2.0 and 5.0°C. This narrowing of the range on the low end is disputed, as will be discussed below.

Uncertainties about ECS are highly consequential for policy making. As will be discussed in Chapter 13, economic models take the ECS value from climate science and use it to project the costs of CO₂ emissions. The traditional ECS value (3.0 °C) has typically yielded modest global social costs of CO₂ emissions, enough to justify some policy actions though mostly deferred to later in the century. If ECS is very high (4.5°C or above) aggressive immediate emission controls become more imperative, whereas values closer to 2.0°C have been shown to imply that no CO₂ emission controls are economically justifiable (Dayaratna et al. 2016, 2020). Obtaining a precise estimate is impossible, so policy making needs to account for the uncertainty.

5.2. Model-based methods of computing climate sensitivity to GHGs

The ECS ranges for the IPCC AR4 and AR5 were obtained primarily by examining the behaviour of climate models. For the AR6 the IPCC changed course and turned to a more direct data-driven methodology. Here we discuss some of the pitfalls of using climate models to try to determine the Earth's climate sensitivity.

ECS represents an emergent property of climate models—that is, it is not directly parameterized or tuned. However, collections of parameterizations are often chosen to produce an expected value of climate sensitivity, particularly with regards to sub-grid-scale cloud processes. Otherwise plausible models and parameter selections have been discarded because of perceived conflict with this warming rate, or aversion to a model's climate sensitivity being outside an accepted range. For example,

Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute climate model (emphasis added):

“We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming; an endeavor which has clearly been successful. Due to the historical order of events, the choice was to do this practically by targeting an ECS of about 3 K using cloud feedbacks, as opposed to tuning the aerosol forcing.”

In other words, the modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

Direct warming from CO₂ doubling is only about 1°C (Hall and Manabe 1997); further warming arises from climate feedbacks that are not explicitly resolved by the model but rely on parameterizations of physical processes. Higher values of ECS arise primarily from positive cloud feedbacks whose magnitude and even sign are very uncertain. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle (Curry and Webster, 1999). It is difficult for climate models to simulate any of these processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks.

ECS can be determined from climate model simulations by doubling the concentration of CO₂ and allowing several centuries for the warming to equilibrate. To avoid the necessity of long simulations, “effective climate sensitivity” is commonly evaluated from a 150-year simulation in response to a sudden quadrupling of CO₂. The spread of ECS values from the CMIP5 climate models (used in the AR5) was 2.0–4.7°C; the spread has increased for the CMIP6 models (used in the AR6) to between 1.8 and 5.7°C (Chen et al, 2021). Far from the science being settled in relation to the response of the climate system to increasing greenhouse gas concentrations, insofar as it is represented by climate models, uncertainties appear to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models (Zelinka et al., 2020)

Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6 (2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying instead on other methods in its assessment instead, chiefly a recent empirical estimate.

5.3. Data-driven methods of computing climate sensitivity to GHGs

Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes,

aerosols) have changed in the past (Otto et al., 2013). Using this information, a simple empirical model called an Energy Balance Model can be estimated. It requires estimating a feedback parameter whose uncertainties are highly amplified in the resulting ECS (Roe and Baker, 2007).

The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and the ocean data is inadequate. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling, or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects need to be estimated to isolate the warming effect of CO₂. Over time, the IPCC's estimate of the cooling effect of aerosols has declined (Lewis 2022).

Paleoclimate proxies are also used to evaluate the sensitivity of past climates, by comparing paleoclimate changes in the Earth's temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today. The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states may not be representative of the current state of the climate system.

A recurring theme in the climate literature is that ECS estimates based on historical data are smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). About 15 estimates based on historical data appeared in the peer-reviewed literature between 2012 and 2024 yielding ECS best estimates between 1.0°C and 2.5°C, although critics have questioned some of the methods and the data quality. For the AR6, the IPCC placed primary weight on the results of Sherwood et al. (2020) that combined historical and paleoclimate proxies and yielded a best estimate of 3.1°C. Lewis (2022) raised a number of concerns about this result, including methodological errors, outdated input values, and use of subjective versus objective Bayesian priors in the analysis. Lewis' analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood et al. analysis – median 2.2°C (1.8–2.7°C in the 17–83 percent likely range, and 1.6–3.2°C in the 5–95 percent very likely range). The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis estimated it to be over 50 percent. The most recent publications on the debate between Sherwood et al. and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

An interesting footnote is that in 1983, the US National Research Council conducted a follow-up study to the 1979 Charney Report, and referring to the estimated sensitivity range of 1.5°C to 4.5°C, said:

“The climate record of the past hundred years and our estimates of CO₂ changes over that period suggest that values in the lower half of this range are more probable.”

Nierenberg et al. (1983 p. 2)

Lewis' analysis likewise implies that climate sensitivity is likely in the lower half of the original 1979 Charney range.

A recent argument, which the IPCC AR6 emphasized, is that data-driven ECS estimates might understate the future warming response to GHGs based on a so-called "pattern effect" (Forster et al 2021). The tropical Pacific is believed to be highly influential on the overall efficiency with which the Earth's climate radiates heat to space, but in some regions heat is more efficiently removed from the climate system than from others. If in a warming climate there is a weakening of the west-to-east temperature gradient in the tropical Pacific, the result would be a concentration of warming in a region where heat is less efficiently removed, raising the ECS of the Earth's climate system. Most climate models simulate that rising GHGs will weaken the east-west temperature gradient, which led the IPCC in the AR6 to conclude that data-driven ECS estimates understated the future ECS value.

However, Seager et al. (2019) pointed out that, contrary to models, the east-west temperature gradient has been strengthening rather than weakening over time. They further argued that the mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic dynamics and there is no reason to expect the gradient to weaken. A similar argument was recently made by Lee et al. (2024), who concluded that "the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere"; in other words, GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate may be lower than current estimates.

5.4. Transient Climate Response

The Transient Climate Response (TCR) is of greater utility in providing an observational constraint on climate sensitivity. TCR is the amount of warming that would occur at the time when CO₂ doubles, having increased gradually by 1 percent each year over a period of 70 years. Relative to the ECS, observationally-determined values of TCR avoid the problems of uncertainties in ocean heat uptake and the fuzzy boundary in defining equilibrium arising from a range of timescales for the longer-term feedback processes (e.g., ice sheets). TCR is more generally related to peak warming and better constrained by historical warming, than ECS. The IPCC AR6 judged the very likely range of TCR to be 1.2–2.4°C. In contrast to ECS, the upper bound of the TCR is more tightly constrained. For comparison, the TCR values determined by Lewis (2023) is 1.25 to 2.0°C, showing much better agreement with the AR6 values than was seen in a comparison of the ECS values.

A related but more flexible parameter is the Transient Response to cumulative carbon Emissions, or TCRE, which relates global temperature change to the cumulative emissions. TCRE is based upon a linear relationship between global average temperature and cumulative emissions, which holds for cumulative emissions of up to 2 teratons of carbon. For a given value of TCRE, we can estimate the amount of warming expected over a future period in response to scenarios of cumulative carbon emission. The IPCC AR6 provides a very likely range for TCRE of 1.0–2.3°C, with a median value of 1.6°C.⁴⁸

As will be discussed in Chapter 6, a real-world ECS below the model average is supported by studies which show climate models on average estimate too much warming at the surface and in the troposphere compared to observations over the past 50 years. Also, lower values align with evidence from consistent fingerprinting (Section 8) that model responses to GHGs need to be scaled down quite a bit to align with observed trends.

5.5. Summary

In the past 5 years, there is a growing realization that climate models are not fit for the purpose of determining the sensitivity of the climate to increasing CO₂ (ECS), owing to the dependence of this sensitivity on poorly resolved processes related to clouds and water vapor.

Data-driven approaches using historical data and paleoclimate reconstructions are now regarded as more reliable for determining ECS, but their reliability is diminished by data inadequacies. The IPCC AR6 upper bound for the likely range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by the paleoclimatic estimates of the ECS. The IPCC AR6 lower bound for the likely range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound of the likely range of ECS has received a substantial challenge from the analysis of Lewis (2022, 2025) that finds the lower bound of the likely range to be 1.75°C with a median value of 2.2°C. Other lines of evidence supporting a lower bound on the ECS range below the IPCC AR6 value are discussed in Chapters 6 and 7.

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6. Models versus Observations in the Recent Past

6.1. Introduction

Climate models are the primary tool used to project future climate changes in response to increasing atmospheric levels of anthropogenic greenhouse gases. They provide the theoretical evidence underpinning energy policy changes, such as efforts to reduce carbon dioxide emissions. In order to determine the value of climate models for this purpose, it is reasonable to ask how well they have reproduced climate variations over the recent past, say the last half-century.

Of great concern is the fact that, after several decades of the climate modeling enterprise involving approximately three dozen models operated by research centers around the world, the range of future warming they produce in response to a hypothetical doubling of atmospheric CO₂ extends over a factor of three. This range of disagreement among models has not changed for decades.

Problems with climate models are not just in their disagreement over the future, but also in their ability to replicate the recent past. Here we review some of the most important metrics of climate model accuracy: ability to reproduce historical surface, tropospheric and stratospheric temperature trends, ability to reproduce the vertical warming profile and ability to reproduce other climate features such as snowfall and humidity. In all cases a persistent finding is that models on average err on the side of too much warming in response to observed historical forcings.

6.2. Surface warming

A straightforward test of climate model validity is its ability to reproduce historical warming in response to known past changes in climate drivers such as greenhouse gases. Figure 6.1 is reproduced from Scaffeta (2023), a peer-reviewed 2023 study which groups the latest-generation (CMIP6) climate models into low ECS (1.5 to 3.0 degrees C), medium ECS (3.0 to 4.5 degrees C) and high ECS (4.5 to 6.0 degrees C), and compares their post-1980 global average temperature simulation ranges to those of three surface temperature records and one satellite-based lower troposphere temperature data product.

Columns correspond to model groups showing low-ECS to high-ECS. Rows correspond to widely-used observed temperature records, the first three showing surface averages and the fourth showing the lower troposphere average. In each panel the yellow area denotes the mean and range ($\pm$ one standard deviation) of climate model simulations for that group. The thick black line shows the observed annual average temperature in the indicated source.

Examination of the leftmost column shows that the low-ECS models track the post-1980 historical warming record reasonably well, but the middle and right columns show that the medium- and high-ECS models conspicuously over-predict the warming.

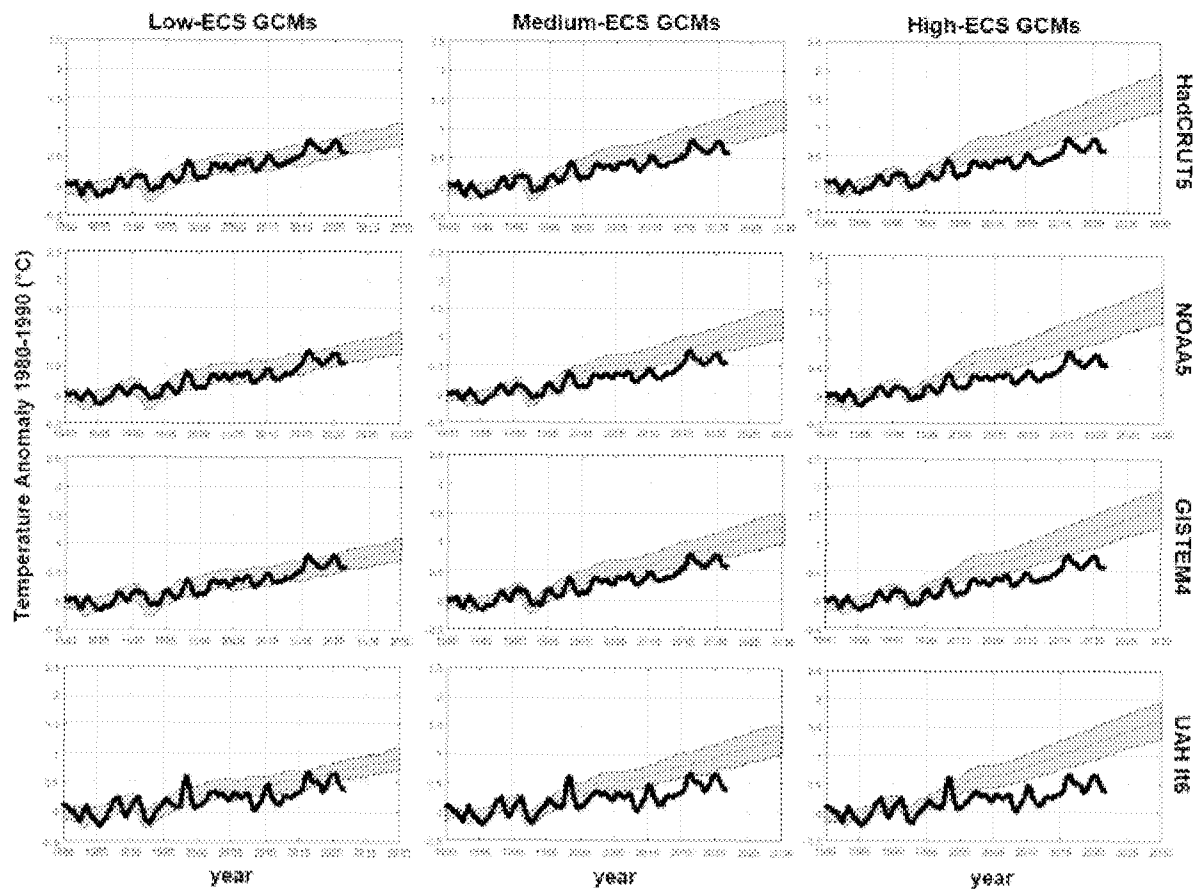
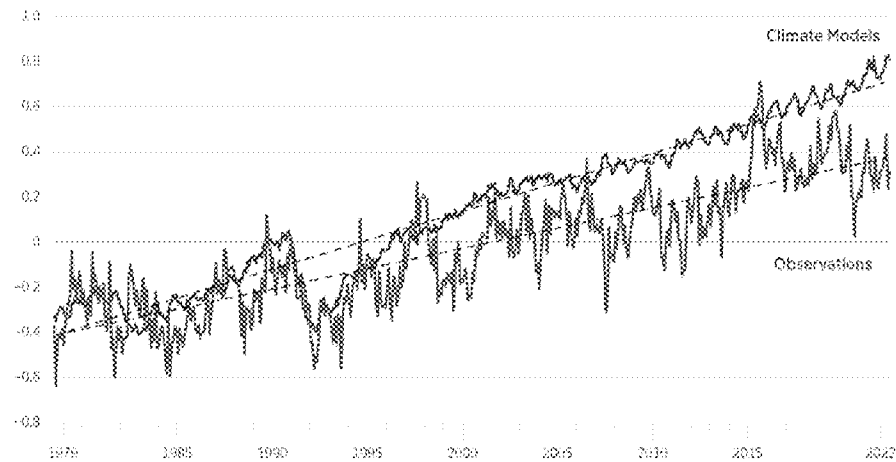


Figure 6.1: model-observational comparisons for Earth's surface warming. Source: Scafetta N. Climate Dynamics 2023 Fig.2. Rows: temperature data products as indicated. Columns: Low- to High-ECS models. Observations: black line. Model simulations: yellow band.

Spencer (2024) has also provided a useful summary of the Model-Observation mismatch by focusing on average surface temperature data products versus the average climate model warming, summarized in Figure 6.2.

Global Average Surface-Air Temperature Variations, 1979~2022

DEPARTURE FROM 1951-2020 AVERAGE, IN DEGREES CELSIUS



NOTE: Figures have been adjusted to align trends starting in 1979.

SOURCES: Authors' calculations based on data from five different observation-based datasets and 35 climate models taking part in the sixth IPCC Climate Model Intercomparison Project, and KNMI Climate Explorer, "Starting Point," <https://climate.knmi.nl/Start.asp> (accessed January 10, 2024).

Figure 6.2: Models versus observations at the surface. Source: Spencer (2024)

6.3. Tropospheric warming

It has long been known that climate models on average overstate warming in the troposphere over the tropics. Since this region generates the bulk of atmospheric warming in a GCM it is important to get the trends right. The discrepancy was flagged as a serious inconsistency in the first US Climate Change Science Program report (Karl et al. 2006) and has been mentioned in every IPCC report since, but it has gotten worse over time not better, and the bias is now global. McKittrick and Christy (2020) compare tropospheric warming rates in CMIP6 climate models to observations from satellites, weather balloons and reanalysis systems (Figure 6.3). Every single model overpredicts the observed warming trend in both Lower- and Mid-Troposphere layers, both globally and in the tropics (Figure 6.4).

In most individual cases the bias is statistically significant and on average it is highly significant. McKittrick and Christy (2020) also show that the bias is larger in high-ECS models, but even the models with lower average ECS predict too much warming. If a group of models were to appear that had a realistic representation of global tropospheric warming, it would likely have to have a lower ECS than even the low-ECS members of the CMIP6 ensemble

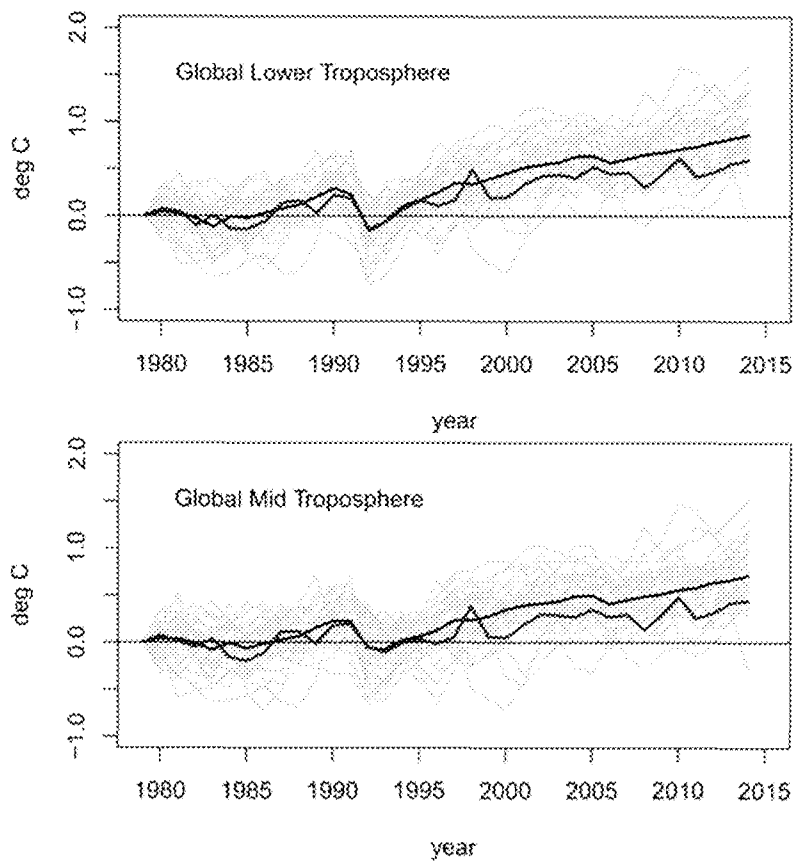


Figure 6.3: Models versus observations in the global troposphere. Source: McKittrick and Christy (2020). Gray lines: model runs. Black: average model run. Blue: average of satellite, radiosonde and reanalysis observations.

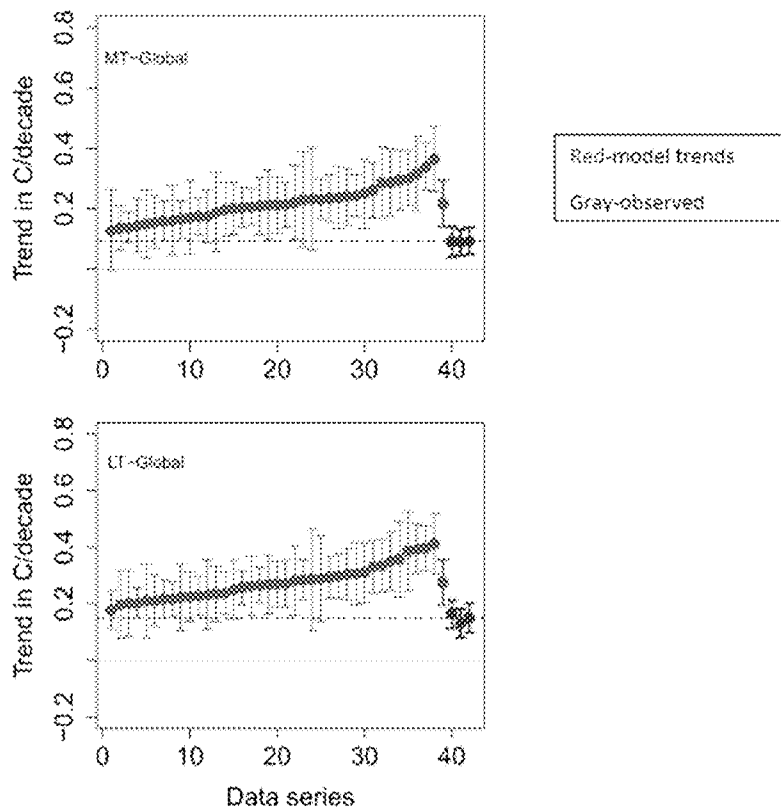


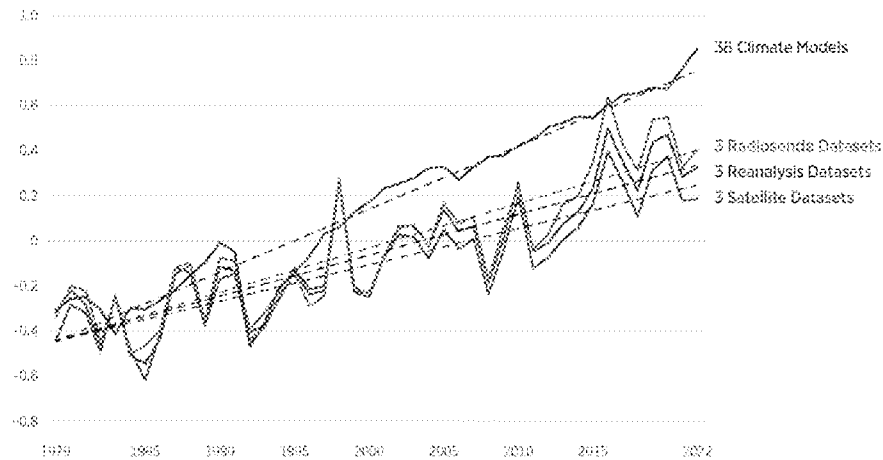
Figure 6.4: Modeled versus observed warming trends in the global troposphere. Adapted from McKittrick and Christy (2020). Red dots: model warming trend in $^{\circ}\text{C}/\text{decade}$ with 95% confidence interval bars. Gray dots: observed warming trends in 3 data products (satellite, radiosondes and reanalysis) and 95% confidence interval bars.

Spencer (2024) shows the mismatch is also present in the lower troposphere:

CHART 3

Global Lower Atmospheric Temperature Variations, 1979~2022

DEPARTURE FROM 1991-2020 AVERAGE, IN DEGREES CELSIUS



NOTE: Figures have been adjusted to align trends starting in 1979.

SOURCES:

- Author's calculations based on data from Ross McKittrick and John Christy, "Persistent Warming Bias in CMIP6 Tropospheric Layers," *Earth and Space Science*, Vol. 7, No. 11 (Nov 14, 2020), <https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2020EF000128> (accessed January 10, 2023).
- Author's calculations based on data from American Meteorological Society, *State of the Climate in 2022*, <https://www.wamweather.gov/index.cfm/analysis/bulletin-of-the-american-meteorological-society-bulletin-of-the-climate/> (accessed January 9, 2023).

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Figure 6.5: Comparison of average trends in lower troposphere, 1979-2022. Source: Spencer (2024).

As mentioned the IPCC has long acknowledged the model-observational mismatch. The AR6 pp. 443-444 confirms model-observational mismatch in the troposphere the tropics (it does not address the global comparison):

Several studies since AR5 have continued to demonstrate an inconsistency between simulated and observed temperature trends in the tropical troposphere, with models simulating more warming than observations (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; McKittrick and Christy, 2018; Po-Chedley et al., 2021)... Over the 1979–2014 period, models are more consistent with observations in the lower troposphere, and least consistent in the upper troposphere around 200 hPa, where biases exceed 0.1°C per decade. Several studies using CMIP6 models suggest that differences in climate sensitivity may be an important factor contributing to the discrepancy between the simulated and observed tropospheric temperature trends (McKittrick and Christy, 2020; Po-Chedley et al., 2021), though it is difficult to deconvolve the influence of climate sensitivity, changes in aerosol forcing and internal variability in contributing to tropospheric warming biases (Po-Chedley et al., 2021). Another study found that the absence of a hypothesized negative tropical cloud feedback could explain half of the upper troposphere warming bias in one model (Mauritsen and Stevens, 2015).

... In summary, studies continue to find that CMIP5 and CMIP6 model simulations warm more than observations in the tropical mid- and upper-troposphere over the 1979–2014 period (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; Suárez-Gutiérrez et al., 2017; McKittrick and Christy, 2018), and that

overestimated surface warming is partially responsible (Mitchell et al., 2013; Po-Chedley et al., 2021). Hence, we assess with *medium confidence* that CMIP5 and CMIP6 models continue to overestimate observed warming in the upper tropical troposphere over the 1979–2014 period by at least 0.1°C per decade,

It is worth noting that despite the enormous accumulation of evidence of excess model warming the IPCC only assigns *medium confidence* to the existence of a warming bias. In other contexts they declare *high confidence* in phenomena established with much less evidence.

6.4. Vertical profile mismatch and excess amplification

An important element of the model-observational discrepancy is the excess amplification with altitude found in climate models. A comparison was shown in the IPCC AR5 Chapter 10, although only in the online supplement. The diagram, reproduced below as Figure 6.6, compares temperature trends by altitude between models and observations, divided up into latitude bands.

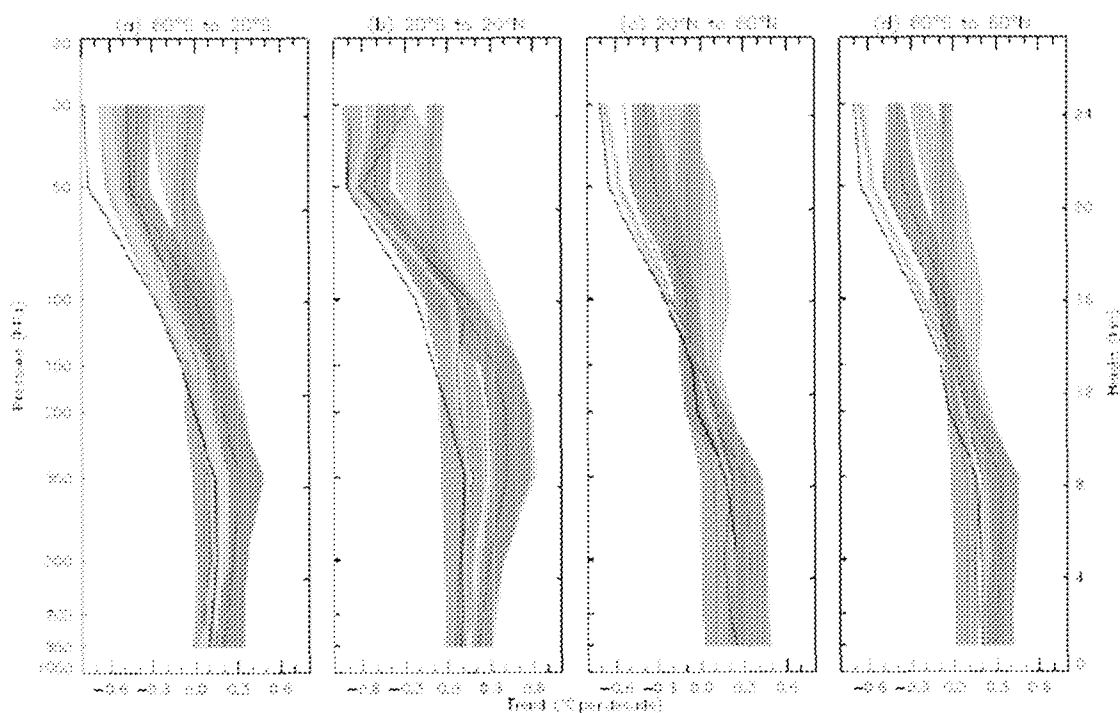


Figure 10.548.1 | Observed and simulated total mean temperature trends from 1979 to 2010 for CMIP5 simulations containing both anthropogenic and natural forcings (red), natural forcings only (blue) and greenhouse gas forcings only (green) where the 5th to 95th percentile ranges of the ensembles are shown. Three representative observations are shown (thick black line: Hadley Centre atmospheric temperature data set 2 (HadAT2), thin black line: Hadwasse (Interpolation of Interim using Mundayas (HadHC06)) 1.5, dark grey band: Hadwasse Interpolation Composite Homogenisation (HIC0-01s, 1.5) ensemble and light grey: HIC0- v 1.5 ensemble. (Adapted from East et al. (2018) but for the more recent period from 1979 to 2010.)

10548-6

Figure 6.6: Vertical warming pattern by latitude band. Source: IPCC AR5 Figure 10.SM.1

The Figure is not referenced in the main report nor in any summary. What it shows, although it is not apparent at first glance, is that the 1979-2010 warming in the lower troposphere is so minimal it is consistent with models having no GHG forcing in them at all, and is inconsistent with the model runs that do have GHG forcing. Here is the main global band (60S to 60N) expanded with the observed trends highlighted in yellow:

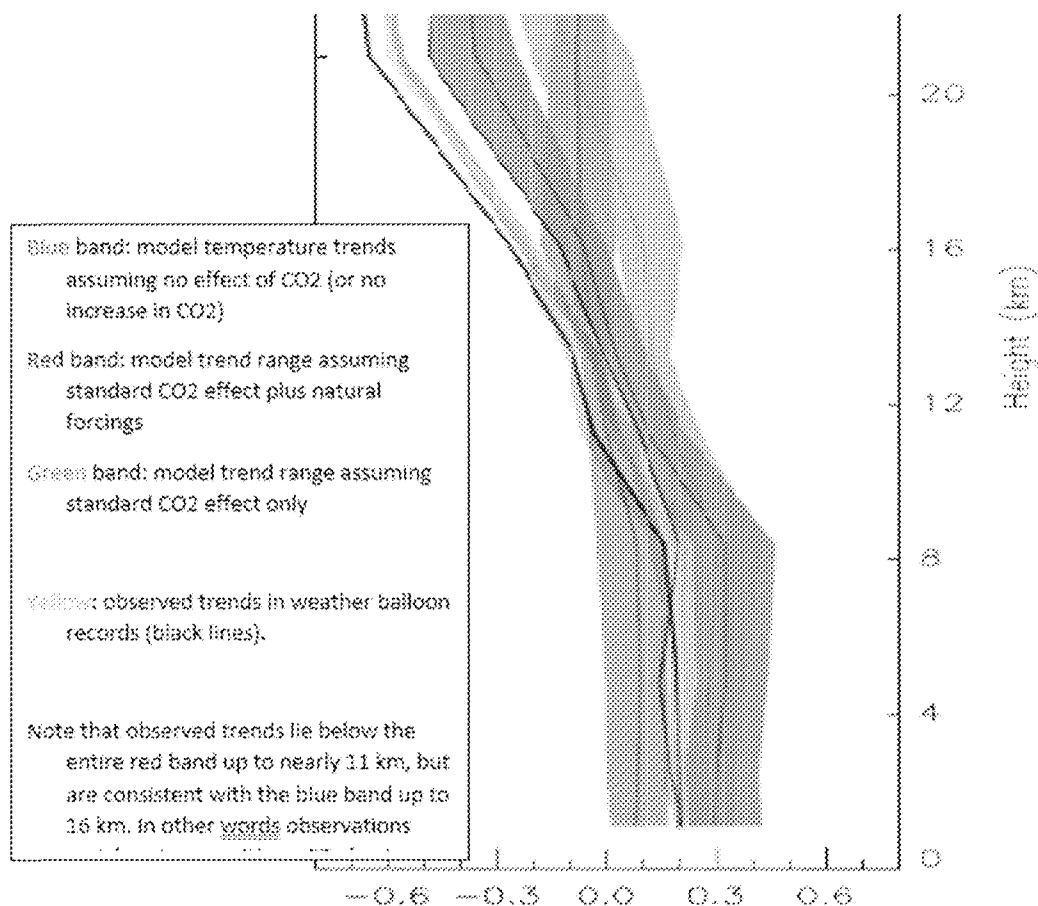


Figure 6.7: Adapted from IPCC AR5 Figure 10.SM.1

The next version of the Figure draws further detail out of the tropics band:

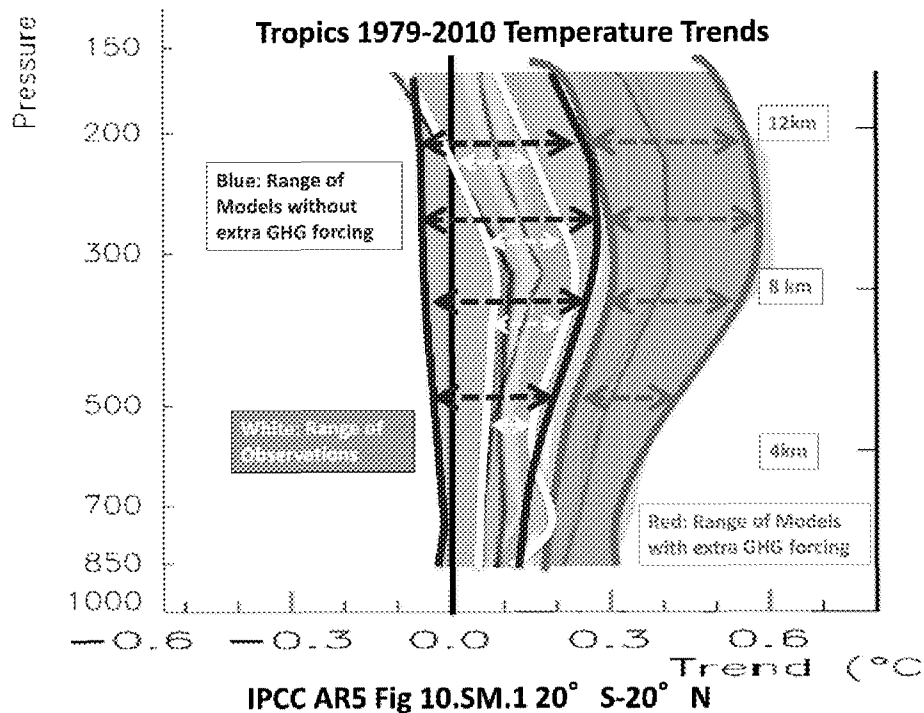


Figure 6.8: Adapted from IPCC AR5 Figure 10.SM.1.

In the tropics, where the models say the warming should be strongest, the observations (shown here in white) lie within the “No CO₂” band and entirely outside the “with CO₂” red envelope. This means that in the entire tropical atmospheric column from the surface to the stratosphere, *observed warming trends are so small they are consistent with the output of models that have no CO₂ warming effect in them, and they are inconsistent with the entire envelope of warming trends generated by models forced with increased CO₂.*

A similar comparison is shown in Christy and McNider (2017), an updated version of which (covering 1979-2024) is reproduced as Figure 6.9. Modeled temperature trends exceed balloon observations from the surface through the top of the troposphere, with observed trends below the entire model range at most pressure levels. Also shown in Figure 6.9 is the TTT layer average from three satellite data products (NOAA, UAH and RSS) compared to the same layer average from climate models for 1979-2024. Again the observed trends lie below the entire model range.

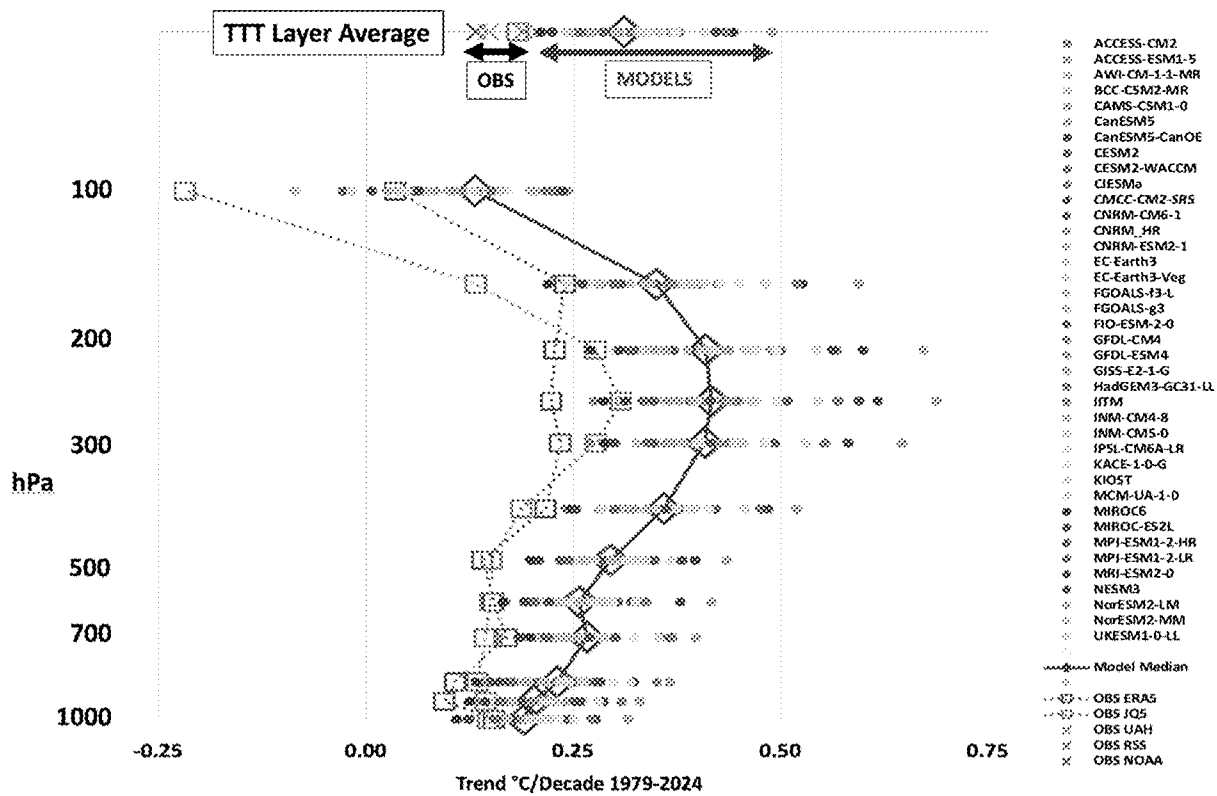


Figure 6.9: Modeled versus observed warming, tropical troposphere. Source: Christy and McNider (2017).

Some defenders of the models have argued that even if there is very little observed warming aloft in the tropics, a “hotspot” still exists in the sense that the warming aloft is greater than at the surface. But there is good evidence that models also exaggerate the amplification rate. Klotzbach et al. (2009), which was not discussed in the AR6, showed that models project greater amplification with altitude than is observed. That paper gave rise to an online debate over whether the amplification rates were being correctly calculated, and whether the discrepancy between models and observations was statistically significant. The topic involves very advanced statistical theory and was dealt with by two experts in time series analysis (Vogelsang and Nawaz 2016) who found that Klotzbach’s conclusions were valid, and that observed amplification is significantly smaller than the model-projected rates. The IPCC AR6 made no mention of this work either.

6.5. Stratospheric cooling

An important element of the expected general “fingerprint” of anthropogenic climate change is simultaneous warming of the troposphere and cooling of the stratosphere. The IPCC AR6 acknowledged that cooling had been observed but only up to 2000. Thereafter the stratosphere has exhibited some warming, contrary to model projections.

The AR6 WG1 Ch 2 pp. 327-9 states (emphasis added):

“Temperatures averaged through the full lower stratosphere (roughly 10–25 km) have decreased over 1980–2019 in all data products, with the bulk of the decrease prior to 2000. The decrease holds even if the influence of the El Chichon (1982) and Pinatubo (1991) volcanic eruptions on the trend, found by Steiner et al. (2020a) to have increased the 1979–2018 cooling trend by 0.06°C per decade, is removed. **Most datasets show no significant or only marginally significant trends over 2000–2019, and the results of Philipona et al. (2018) show weak increases over 2000–2015** in the very lowermost stratosphere sampled by radiosondes....

It is virtually certain that the lower stratosphere has cooled since the mid-20th century. However, most datasets show that **lower stratospheric temperatures have stabilized since the mid-1990s with no significant change over the last 20 years**. It is likely that middle and upper stratospheric temperatures have decreased since 1980, but there is low confidence in the magnitude.

The cited source, Philipona et al. (2018), in an article entitled “Radiosondes Show That After Decades of Cooling, the Lower Stratosphere Is Now Warming”, stated:

“In response to continued greenhouse gas increases and stratospheric ozone depletion, climate models project continued tropospheric warming and stratospheric cooling over the coming decades. Global average satellite observations of lower stratospheric temperatures exhibit no significant trends since the turn of the century. In contrast, an analysis of vertically resolved radiosonde measurements from 60 stations shows an increase of lower stratospheric temperature since the turn of the century at altitudes between 15 and 30 km and over most continents. Trend estimates are somewhat sensitive to homogeneity assessment choices, but all investigated radiosonde data sets suggest a change from late twentieth century cooling to early 21st century warming in the lower stratosphere.”

6.6. Water vapour trends

Much of the warming in climate models derives not from GHG increases themselves but from water vapour feedbacks: extra warming induced by the projected accumulation of water vapour in the atmosphere after it warms due to CO₂. But new evidence (Simpson et al. 2024) shows that models have over-projected increases in humidity.

“Water vapor in the atmosphere is expected to rise with warming because a warmer atmosphere can hold more moisture. However, over the last four decades, near-surface water vapor has not increased over arid and semi-arid regions. This is contrary to all climate model simulations in which it rises at a rate close to theoretical expectations, even over dry regions. This may indicate a major model misrepresentation of hydroclimate-related processes; models increase water vapor to satisfy the increased atmospheric demand, while this has not happened in reality.”

(Simpson et al. 2024)

While the models and observations matched over the 1988 to 2006 interval they diverge after that, directly contradicting model projections.

6.7. Snow cover

According to the Rutgers University Snow Lab (undated) the Northern Hemisphere winter snow cover shows an increasing trend over time.

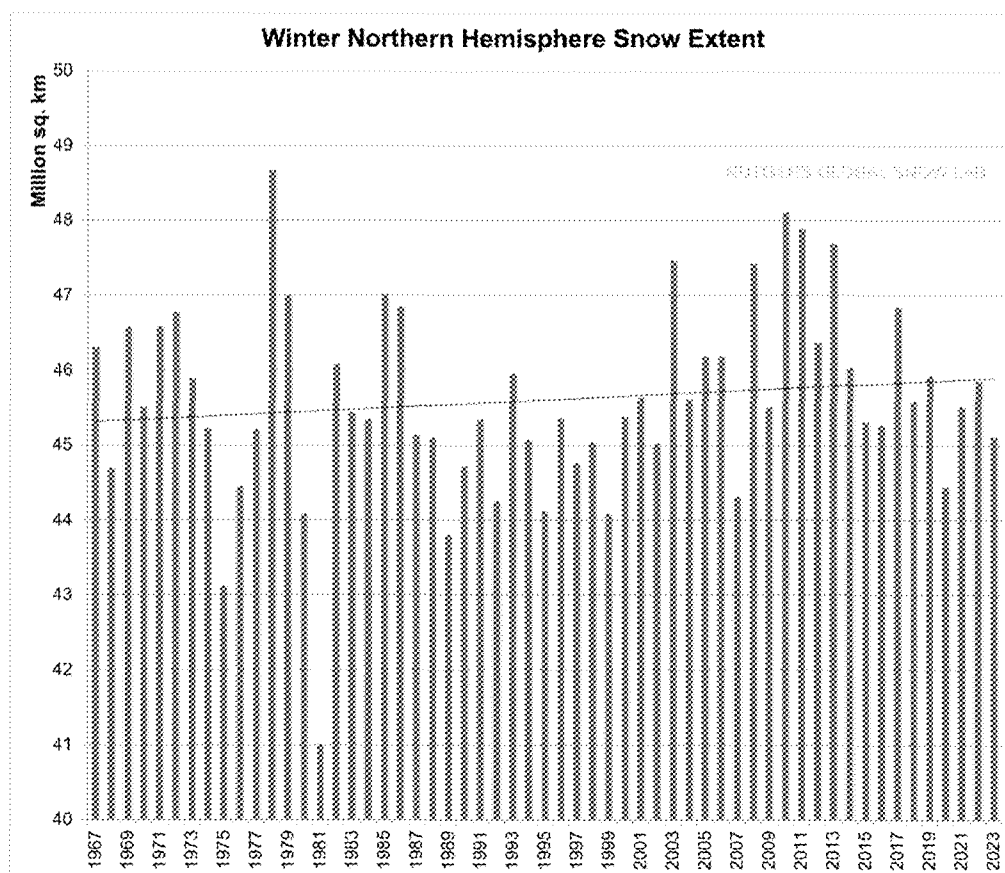


Figure 6.10: Northern Hemisphere Winter Snow extent. Source: https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhl&ui_season=1 (February 24, 2024)

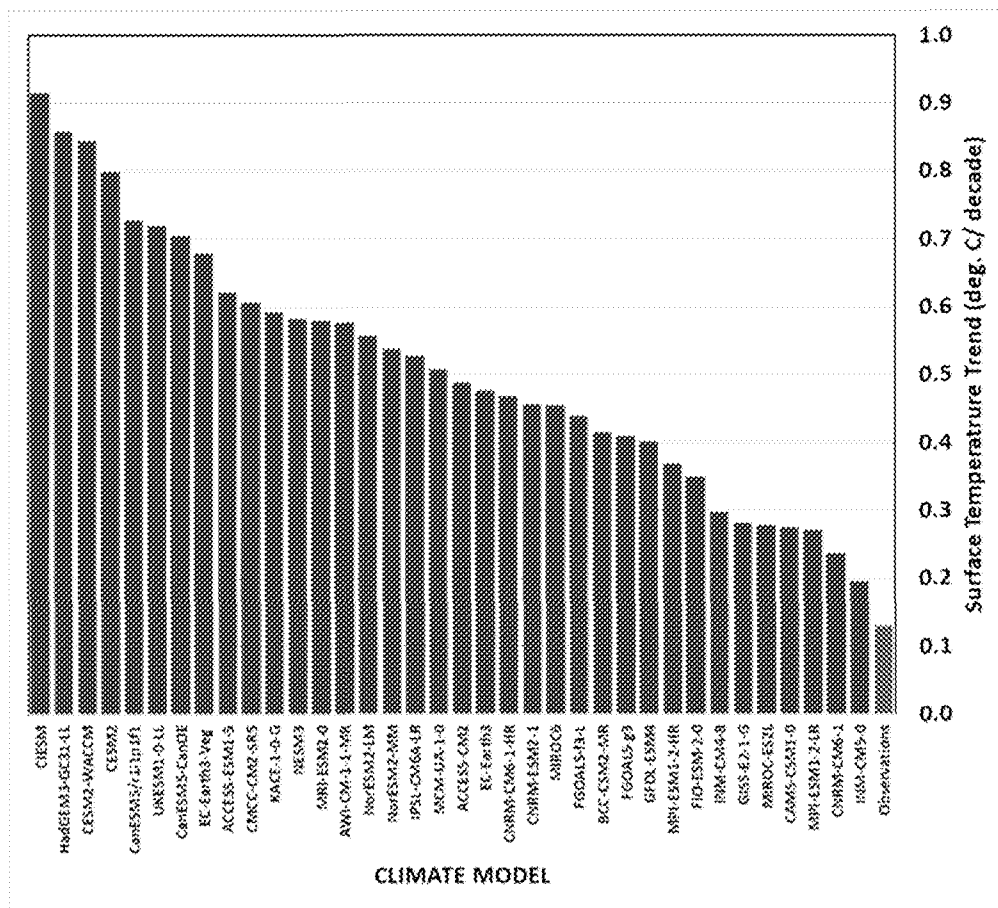
Models project declining Northern Hemisphere snow cover due to climate warming. But observations do not support this, as explained by Connolly et al. (2019).

Observed changes in Northern Hemisphere snow cover from satellite records were compared to those predicted by all available Coupled Model Intercomparison Project Phase 5 (“CMIP5”) climate models over the duration of the satellite’s records, i.e., 1967–2018. A total of 196 climate model runs were analyzed (taken from 24 climate models). Separate analyses were conducted for the annual averages and for each of the seasons (winter, spring, summer, and autumn/fall). A longer record (1922–2018) for the spring season which combines ground-based measurements with satellite measurements was also compared to the model outputs. **The climate models were found to poorly explain the observed trends. While the models suggest snow cover should have steadily decreased for all four seasons, only spring and summer exhibited a long-term decrease, and the pattern of the observed decreases for these seasons was quite different from the modelled predictions.** Moreover, the observed trends for autumn and winter suggest a long-term increase, although these trends were not statistically significant.

Connolly et al. (2019), emphasis added.

6.8. US Corn Belt

One of the largest discrepancies between models and observations can be found when we test them in a region of particular importance to global food production: the U.S. Corn Belt. Fig. 6.11 shows the warming trends for summertime (June, July, August) for the U.S. 12-state Corn Belt (IN, IA, NE, ND, SD, MO, MN, WI, MI, OH, KS, NE) during 1973-2022. All 36 climate models (red) produced too much warming compared to observations (blue) during 1973 to 2022.



- The warm bias discussed here is consistent with independent evidence of model bias presented in Chapters 5 (measuring climate sensitivity) and 7 (optimal fingerprinting). Given the persistent warm bias in so many key aspects of climate model performance, users are justified in assuming that projections of future warming are also very likely to be biased too warm.

7. Uncertainties in Climate Change Attribution

7.1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) distinguishes between detection of climate change and attribution of cause. As defined by the IPCC AR6 WGI Glossary (IPCC, 2025):

Detection: "Detection of change is defined as the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense, without providing a reason for that change. An identified change is detected in observations if its likelihood of occurrence by chance due to internal variability alone is determined to be small, for example, <10%."

Attribution: "Attribution is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with a formal assessment of confidence."

Both steps rely on statistical analysis. Detection focuses on whether changes are significant enough to stand out from random variation regardless of cause. Attribution involves comparison of observed events to model-generated counterfactuals. Since experimentation on the climate is not possible attribution requires statistical inference to assess how much human activities, such as GHG emissions, versus natural factors, like volcanic eruptions, explain observed changes. Attribution methods assume all external and internal drivers of the system are known and represented.

There are ongoing scientific debates around attribution methods, especially for attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement. The Fourth Assessment Report: The Physical Science Basis (Hegerl et al., 2007) explained it as follows:

'Attribution' of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence... unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is 'consistent with the estimated responses to the given combination of anthropogenic and natural forcing' and 'not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings' (IPCC, 2001)... The approaches used in detection and attribution research described above cannot fully account for all uncertainties, and thus ultimately expert judgement is required to give a calibrated assessment of whether a specific cause is responsible for a given climate change.

The Fifth Assessment Report Working Group II makes the following statement: (Cramer et al., 2014):

"Two broad challenges to the detection and attribution of climate change impacts relate to observations and process understanding. On the observational side, high-quality, long-term data relating to natural and human systems and the multiple factors affecting them are rare. In addition, the detection and

attribution of climate change impacts requires an understanding of the processes by which climate change, in conjunction with other factors, may affect the system in question.”

Because of the complexity of the causal chains in the climate system, investigation of these relationships is exceptionally challenging.

7.2 Attribution methods

The Intergovernmental Panel on Climate Change (IPCC) employs several attribution methods to assess the causes of observed climate changes, distinguishing between natural and human-induced factors. Below is a concise description of the key methods that have been used by the IPCC:

Optimal Fingerprinting uses linear regression to explain variations in observed climate data as a weighted sum of climate model simulations run with and without anthropogenic forcings. The data used in the regression model are weighted to try to minimize the influence of random noise and the estimation method is chosen to take account of climate model error.

Time Series Analysis exploits statistical differences between anthropogenic forcing and natural variability to see which one dominates observed temperatures, and also uses variations in the timing of changes to determine if causal dependence across data series can be inferred.

Process-Based Attribution focuses on understanding the physical mechanisms behind observed changes. This approach combines observations, climate models, and theoretical understanding to attribute changes in specific processes to forcings. This approach is often used for regional climate phenomena, such as monsoon changes or polar amplification

Extreme Event Attribution assesses in the role of human influence in the likelihood of occurrence or intensity of extreme weather events (e.g. heat waves, droughts). Methods include:

Probabilistic Event Attribution uses large ensembles of climate model simulations to compare observed events to model-generated counterfactuals

Storyline Approach examines the physical processes driving an event and evaluates how anthropogenic forcings may have modified those processes

7.3 Attribution of global warming

Attribution statements for global warming in the three most recent IPCC Assessment reports are:

AR4: “Most of the observed increase in global average temperatures since the mid-20th century is *very likely* due to the observed increase in anthropogenic greenhouse gas concentrations.” (IPCC, 2007)

AR5: “It is *extremely likely* that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas

concentrations and other anthropogenic forcings together. The best estimate of the human- induced contribution to warming is similar to the observed warming over this period.” (IPCC, 2013)

AR6: “The *likely* range of total human-caused global surface temperature increase from 1850–1900 to 2010–2019 is 0.8°C to 1.3°C, with a best estimate of 1.07°C. It is *likely* that well-mixed GHGs contributed a warming of 1.0°C to 2.0°C, other human drivers (principally aerosols) contributed a cooling of 0.0°C to 0.8°C, natural drivers changed global surface temperature by –0.1°C to +0.1°C, and internal variability changed it by –0.2°C to +0.2°C. It is *very likely* that well-mixed GHGs were the main driver of tropospheric warming since 1979.” (IPCC, 2021)

The AR4 and AR5 attribution statements reference the warming since the mid-20th century, the period when greenhouse gas emissions began rapidly increasing. The words “most” and “more than half” are deliberately imprecise, potentially ranging from 51 to 99% of the warming – presumably this imprecision is to account for structural uncertainties such as natural internal variability. The confidence level increases from *very likely* to *extremely likely* from AR4 to AR5. The structure of the attribution statement in the AR6 is fundamentally different, referencing the warming to the period 1850-1900. The AR6 attribution statement is more precise numerically, but with a lower level of confidence at “likely” – the AR6 attributes essentially all of the warming to increases in greenhouse gases. The most confident statement from the AR6 relates to the tropospheric warming since 1979, using the words “main driver” and “*very likely*.”

There are three areas of substantive criticism of the IPCC assessment of the causes of the recent warming: inadequate assessment of natural climate variability, inappropriate statistical methods, and substantial discrepancies between models and observations. The latter is discussed in Chapter 7. The other two factors are discussed herein. Both of these issues are relevant not only in context of the main policy-relevant statement of the IPCC concerning attribution of the recent warming, but also because the global warming attribution provides the basis for extreme event attribution

7.2. Natural climate variability

The IPCC AR6 states that natural external drivers since 1850-1900 have changed global surface temperature by –0.1°C to +0.1°C, and internal variability has changed it by –0.2°C to +0.2°C – on average, having essentially no net impact on the warming since 1850-1900. This assessment of the contributions of natural variability has been disputed by a number of publications that question the magnitudes of the contributions from solar forcing and internal variability from the large-scale ocean circulations (R Connolly et al., 2021; W Soon, 2023).

If the Equilibrium Climate Sensitivity to CO₂ is low (Chapter 5), then natural climate variability becomes more important in the attribution of the recent warming. Further, if natural variability is higher, then estimates of the Equilibrium Climate Sensitivity from the historical period would be lower (Scafetta, 2023).

Solar variability

The IPCC AR5 concluded that the best estimate of radiative forcing due to Total Solar Irradiance (TSI) changes for the period 1750–2011 was 0.05 W/m^2 (Myrhe et al., 2014). The IPCC AR6 acknowledges a much larger range of estimates of changes in TSI over the last several centuries, stating that the TSI between the Maunder Minimum (1645–1715) and the second half of the twentieth century increased by $0.7\text{--}2.7 \text{ W/m}^2$, a range that includes both low and high variability TSI data sets (Gulev, 2021). However, the recommended forcing dataset for the CMIP6 climate model simulations used in the AR6 for attribution studies averages two data sets with low solar variability (Matthes, 2017).

While the IPCC AR6 shows a substantially greater solar impact than does the AR5, the overall impact on the climate was assessed to be small compared to anthropogenic forcing of climate change. However, the impact of solar variations on the climate is uncertain and subject to substantial debate – something that you would not infer from the IPCC assessment reports (Lockwood, 2012; Connolly et al., 2021).

Exactly how TSI has changed over time has been a challenging problem to resolve. Since 1978, there have been direct measurements of TSI from satellites. However, the data exhibit non-negligible inconsistencies, and interpreting any multi-decadal trends in TSI requires comparisons of observations from overlapping satellites. There are several rival composite TSI datasets, disagreeing as to whether TSI increased or decreased during the period 1986–96 (the ACRIM gap; see Chapter 4). Further, the satellite record of TSI is used for calibrating proxy models, whereby past solar variations are inferred from sunspots and cosmogenic isotope measurements (Velasco Herrera et al., 2015).

There is substantial evidence for high solar activity in the second half of the 20th century (starting in 1959) and extending into the 1990's, before a decline in the early 21st century; this period is often termed the “Modern Maximum.” (Chatzistergos et al., 2023; Solanki et al., 2004; Usoskin et al., 2007). However, some scientists have concluded that it is not possible to be confident of any multi-decadal trend in TSI (Schmutz, 2021).

As a result of this uncertainty, some reconstructions for past values of TSI (since 1750) have low variability, implying a very low impact of solar variations on global mean surface temperature, whereas datasets with high TSI variability can explain more than 70% percent of the temperature variability since preindustrial times (Scafetta, 2013; Stefani, 2021). Hence, the choice of which TSI satellite record used in an analysis can substantially influence how much climate change is attributed to human versus natural forcings.

There is growing evidence that other aspects of solar variability, which are referred to as solar indirect effects, amplify TSI forcing or are independent of TSI forcing. Scafetta et al. (2023) suggests that ~80% of solar influence on climate may stem from non-TSI mechanisms. Candidate processes include: solar ultraviolet changes; energetic particle precipitation; atmospheric-electric-field effect on cloud cover; cloud changes produced by solar-modulated galactic cosmic rays; large relative changes in the magnetic field; and the strength of the solar wind. Solar indirect effects are not included in climate models, although indirect methods of estimating these effects suggest significant influence. However, claims of non-TSI mechanisms influencing climate are uncertain and debated.

Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns. These circulation patterns include the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation (ENSO). These circulation patterns influence ocean heat uptake and heat distribution, and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astronomical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, the simulated magnitude in the multi-decadal band is too low in most models relative to observations, and the phasing of the variability in long-term climate simulations is not synced with the actual, observed climate variations (Kravtsov et al. 2024). Averaging multiple simulations from climate models effectively averages out the internal variations, leaving only the forced climate variability (e.g., CO₂ forcing). With most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the IPCC AR5 and AR6 reports:

"Decadal variability in the Pacific, associated with the PDO or IPO, contributes significantly to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations." (IPCC, 2013)

"Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (high confidence)." (IPCC, 2021)

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: "The likely range of change due to internal variability is -0.2°C to +0.2°C (IPCC, 2021)." This implies a trough-to-peak change of 0.4°C. Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the 50 years since 1975, during which most of the warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the timing of the peaks and troughs is not adequately simulated, with each model and individual ensemble simulating a different phasing. Once the simulations of the ensemble members and different models are averaged, the natural internal variability contribution is averaged out, effectively cancelling the role of natural internal variability in the attribution process.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate

patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947–1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns including the frequencies of El Niño and La Niña events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming (REF TO A FIG OF GLOBAL TEMP ANOMALIES ELSEWHERE IN DOC) When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, it has been found that 40 percent or more of the warming in the second half of the 20th century was caused by natural internal variability (McLean et al., 2009; Tung and Zhou, 2013; Chylek et al., 2016; Scafetta, 2021).

7.3. Optimal fingerprinting

Optimal fingerprinting is a statistical technique introduced by Allen and Tett (1999) that compares observed climate data to climate model simulations to identify patterns (or "fingerprints") associated with human or natural forcing. It involves taking a vector of observed climate changes, such as warming rates in locations around the world, and decomposing them into a weighted sum of "signals", which are analogues to the observations generated by climate models with different types of forcings. The weights are chosen using a regression method called Total Least Squares. The analysis commonly uses just two signals, one generated by models using only anthropogenic forcings and one using only natural forcings. If the estimated weighting coefficient attached to a signal is significantly different from zero, then that signal is said to be "detected". If it is close to 1.0, then the model generating the signal is said to be consistent with observations. If it is less than 1.0, then the model signal for that forcing is too strong and needs to be scaled down, and vice-versa. Both the observed data and the signals are weighted using a model-generated estimate of patterns of randomness in the climate system so as, in principle, to put maximum weight on regions where natural variability is minimized.

Optimal fingerprinting is the primary tool for attribution in the climate literature. Studies applying it have been cited thousands of times, and it has been prominently featured by the IPCC since the 2001 Third Assessment Report. One of its inherent weaknesses is that results depend on assumptions about the accuracy of climate models, especially regarding their representation of natural variability (IPCC AR5 Ch 10.2.3).

Additionally, a series of papers by McKittrick (McKittrick 2022a, 2022b, 2023, 2025) has challenged the optimal fingerprinting method, arguing that it is inherently unreliable and that commonly used practices in econometrics can provide more valid results. Statistical theory requires that for regression models to yield unbiased coefficients, a set of assumptions called the Gauss-Markov conditions must hold. McKittrick (2022a) argued that the Allen and Tett (1999) methodology violates the Gauss-Markov conditions, leading to potentially biased and inconsistent fingerprinting coefficients, undermining the reliability of the method. Chen et al. (2023) confirmed this analysis and argued that the method could yield unbiased results but only under very stringent assumptions. McKittrick (2022b) and (2023) raised a further concern that climate scientists—virtually alone among scientific disciplines—have used an estimation method called Total Least Squares (TLS) to estimate anthropogenic greenhouse gas signal coefficients, despite its tendency to be unreliable unless some strong assumptions hold that in practice are unlikely to be true. Under conditions which easily arise in optimal fingerprinting, TLS yields estimates with large

positive biases. Thus, any study that has used TLS for optimal fingerprinting without verifying that it is appropriate in the specific data context has likely overstated the result.

McKittrick (2025) presented an empirical example comparing the results of conventional optimal fingerprinting against methods drawn from mainstream econometrics which are known to be valid for the specific application of signal detection. While the IPCC optimal fingerprinting method yields an anthropogenic signal coefficient close to 1.0 on a global temperature data set spanning 1900 to 2010, consistent estimation yields a coefficient around 0.4, which rises to about 0.65 on data spanning 1980 to 2010, implying the model response to greenhouse gases needs to be scaled down by about half to optimally match observations. The natural forcing signal coefficient, by contrast, is between 2.0 and 4.0, implying the climate model signals of natural forcing need to be scaled up two-to four-fold to match observed climate change. The fingerprinting coefficients estimated in McKittrick (2025), when used to scale the average sensitivity of the climate models used to generate the forcing signals in his data set, imply a Transient Climate Sensitivity of 1.4°C, which matches the estimate by Lewis (2022) using a different estimation method and multiple independent data sets.

While these analyses do not prove that all of the results from using the IPCC optimal fingerprinting method are wrong, it does show that the basis on which they were believed to be correct is non-existent – hence reducing confidence in the results.

7.4. Time series methods

The IPCC (AR5 WGI 10.2.2) drew attention to alternative approaches of assessing causality that emerged from the time series econometrics literature. They have the advantage of not depending on assumptions about the accuracy of climate models, but their disadvantage is they depend on assumptions about the data generating process underlying climate and forcing data that are not straightforward to test. The methods, now referred to as climate econometrics, use the tools of unit root testing, Granger causality and cointegration analysis, all of which are familiar in economics and finance and which are slowly being adopted in climate science. Time series analysis methods hold out the possibility of determining whether anthropogenic or natural forcings are the primary drivers of climate change without requiring the use of climate models, although key questions remain unsettled (e.g. Dergiades et al. 2016, Balcombe et al. 2019, Dagsvik et al. 2020, Razzak 2022, Dagsvik and Moen 2023).

Granger causality modeling is a tool for determining directions of influence in data series that move together. “Granger causality” is a statistical, not a physical, concept. If knowing the current value of one variable significantly improves the forecast accuracy of another variable we can infer a causal connection exists; this is called Granger causality. The modeling tools, called vector autoregression, measure direct impulse-response patterns and feedbacks. An application to the well-known Vostok ice core data revealed an error by Al Gore in his documentary *An Inconvenient Truth*. Gore showed the data and drew attention to the coherence of temperature and CO₂ changes over a 440,000 year span, which he asserted was due to CO₂ driving temperature changes. But temperature changes can also affect atmospheric CO₂ levels. Davidson et al. (2015) examined the series and found that temperature Granger causes CO₂ but not the reverse. In other words on the time scales represented in the Vostok data the coherence in the

series is primarily due to the influence of temperature on CO₂ levels not the feedback going from CO₂ to temperature.

In summary, the main statistical methods for attributing causation in climate data are optimal fingerprinting and time series analysis. Applications of the Allen and Tett (1999) optimal fingerprinting method dominate the attribution literature and have underpinned past IPCC conclusions, but results depend on the accuracy of climate models and the method has recently been criticized as inherently biased. Time series methods do not depend on climate models but require assumptions of their own and have generated results that have thus far not converged on a consensus.

7.5. Extreme event attribution (EEA)

The IPCC AR6 provides an ambiguous assessment of the role of global warming in the historical record of extreme weather and climate events. Chapter 11 of WG1 states (Seneviratne et al., 2021):

“Evidence of observed changes in extremes and their attribution to human influence (including greenhouse gas and aerosol emissions and land-use changes) has strengthened since AR5, in particular for extreme precipitation, droughts, tropical cyclones and compound extremes (including dry/hot events and fire weather). Some recent hot extreme events would have been extremely unlikely to occur without human influence on the climate system.”

By contrast, Chapter 12 of WG1 (Table 12.12) paints a different picture – presumably, the expert judgment of different groups of authors for the two chapters came to different conclusions (Ranasinghe, 2021):

High confidence in an increase in extreme heat events in tropical regions where observations allow trend estimation and in most regions in the mid-latitudes, medium confidence elsewhere

Medium confidence in a decrease in extreme cold events in Australia, Africa and most of northern South America where observations allow trend estimation

No evidence of emergence in the historical period of a change in river floods, heavy precipitation, drought, fire weather, severe wind storms, and tropical cyclones

While the overall issue of detecting changes in extreme weather events and their attribution remains ambiguous, most of the activity in this area relates to the attribution of single extreme weather events. The most prominent effort is the World Weather Attribution (WWA; worldweatherattribution.org), which is an international research initiative that focuses on extreme event attribution analyzing how climate change influences the likelihood and intensity of extreme weather events. The approach used by the WWA runs large ensembles of regional climate models to compare the event in today’s climate, versus a pre-industrial counterfactual climate without human-caused warming.

WWA plays a prominent role in linking extreme weather to climate change and its press releases attract considerable public and policy discussions. However, the WWA’s tendency to promote non-peer-

reviewed findings, funding ties, open admission that they shape their analyses to serve purposes of litigation and other methodological challenges have sparked controversies, with critics questioning the robustness and impartiality of its conclusions (Pielke Jr. 2024). Despite these issues, WWA's work continues to shape climate science and media narratives. Technical criticisms of the approach include: neglect of a formal detection process; an implicit assumption that 100% of the post-industrial warming is caused by CO₂; and failure to adequately account for natural internal climate variability.

Because EEA is relatively new many basic methodological issues have yet to be settled in the expert literature. An important challenge is the lack of data. Extreme events are by definition rare. Many analyses of extreme event types (including the US National Assessment Reports) only evaluate data since 1950 or 1970. However, as emphasized by Chapter 8, many of the worst extreme weather and climate events in U.S. history occurred prior to the first half of the 20th century including in the early 19th century. And if paleoclimate reconstructions are considered, it becomes very difficult for an event to pass the detection thresholds of exceeding what is expected from natural variability, particularly if a reasonably sized geographic region is considered.

Another challenge is defining the event under study. There is a longstanding literature in statistics and econometrics on the challenge of analyzing data with outliers. The issue arises because a data series establishes a probability distribution defining the expected range of observations. If an outlier is observed it might indicate that the underlying process giving rise to the data distribution has changed (which in the weather context would mean a climatic change has been detected) or that the underlying process has multiple regimes each with a different probability distribution, in which case observing an outlier simply means we were temporarily in a different regime, but the system itself was unchanged. If a time series contains only a single outlier event at the end of the series it is not possible to determine which model is the correct one (Chen and Liu 1993). For instance, there might be an "ordinary" weather regime that yields a distribution of summer daytime highs in a particular coastal region, and a second "heatwave" regime that kicks in when an inland blocking event occurs, which yields a temperature distribution centered 15°C higher than the first one. A day with temperatures 13°C above normal would either be an extreme heat anomaly under the first regime or a somewhat cool event under the second, and we have no way in this case of knowing on statistical grounds which view is correct.

Visser and Petersen (2012) and Sardeshmukh et al. (2015) both point out that different distributions may fit observed data equally well but yield very different implications about the likelihood of a specific weather event. Visser and Petersen argue that, in view of the deep uncertainties of extreme weather analysis drawing a connection between individual events and global climate change should be avoided. Furthermore the existence of an outlier at the end of a data series poses the problem that estimates of the event probabilities will be biased whether the outlier is included or excluded (Barlow et al. 2020). Methods to eliminate the bias have not yet been established, leading some experts (e.g. Miralles and Davison 2023) to argue that in settings in which a data series contains a single extreme event at the end, estimation of a return period for the extreme event will be so biased and uncertain it should be avoided altogether.

In spite of these concerns, the U.S. is presently considering something like the WWA, which is being investigated by a NASEM Panel on Attribution of Extreme Weather and Climate Events and their impacts (NASEM, 2025).

A case studies from a recent high impact extreme events in the U.S. is provided to illustrate the challenges and ambiguities in attributing the frequency and intensity of extreme weather events to human-caused warming.

7.6. Case study – 2021 Western North America heat wave

The 2021 Western North America heat wave was an extreme heat wave that affected much of Western North America in late June 2021. In particular, surface temperature records were set in Portland, OR (116°F; previous record 107°F) and Seattle, WA (108 °F; previous record 103°F) (Mass et al., 2024).

The WWA team garnered international headlines for their analysis and provided the following attribution statements (WWA, 2021; Philip et al., 2022):

Based on observations and modeling, the occurrence of this heatwave was virtually impossible without human-caused climate change.

The event is estimated to be about a 1 in 1000-year event in today's climate.

The event would have been at least 150 times rarer without human-induced climate change.

This heatwave was about 2°C hotter than it would have been if it had occurred at the beginning of the industrial revolution (when global mean temperatures were 1.2°C cooler than today).

But an important caveat to the first claim is that other researchers concluded, based on historical weather data, that while a heat wave of the magnitude observed was indeed virtually impossible without anthropogenic climate change, it was also virtually impossible *with* climate change. Bercos-Hickey (2022) noted “these temperatures were virtually impossible under any previously experienced meteorological conditions, with or without global warming.” McKinnon and Simpson (2022) stated “the most likely explanation remains that the weather event itself was ‘bad luck.’” The 2023 Oregon Climate Assessment (Fleischman 2023) concluded that the heat dome would have formed even without climate change and “There is no evidence that the highly unusual combination of weather features that drove the heat dome were made more likely by climate change, and climate models do not project an increase in the frequency of high-pressure ridges over the Pacific Northwest” (Fleischman 2023 p. 49).

Mass et al. (2024) summarizes the proximate sequence of compound events leading to the heat wave. There was a record-breaking midtropospheric ridge over the Pacific Northwest, forced by a tropical disturbance in the western Pacific. This produced record-breaking midtropospheric temperatures, strong subsidence in the lower atmosphere, low-level easterly flow that produced downslope warming on regional terrain and the removal of cooler marine air, and an approaching low-level trough that enhanced downslope flow. The event occurred at a time of maximum solar insolation, and drier-than-normal soil moisture. Using a storyline approach, Mass et al. assessed that there is no trend in drought and dry soils in the Pacific Northwest; there is no evidence of global warming producing stronger ridges of high pressure, and no observed trend in heat waves or record temperatures in the region. They

concluded that although anthropogenic warming may have contributed as much as 2°F to the magnitude of the event, there is little evidence of further amplification of the event from increasing greenhouse gases.

A statistical analysis of a model-based attribution study of this heat wave was conducted by Bercos-Hickey et al. (2022). Because this event is a far outlier and far above the bounds of Generalized Extreme Value distributions fitted from historical data, they concluded that estimates of return times, quantitative changes in event magnitude and frequency, and probability of the extreme temperatures such as provided by the WWA are not accurate and should be interpreted as having low confidence. They found that hindcast attribution methods using an ensemble of regional climate models, combined with Pearl (2009) causal inferences, can provide limited and conditional information about the magnitude of the human influence on this heatwave – they provided a more highly constrained estimate that human activities caused a ~1.4°C–1.8°F increase in the daily maximum temperatures.

Zeder et al. (2023) also concluded that the methods employed by Philip et al. (2022) tend to overstate the rarity of extreme heat waves, leading to a biased perception of the effect of climate change on the heatwave event: “The tendency to overestimate the return period of observed extreme heatwave events may fuel the impression that seemingly impossible heatwave extremes are currently clustering at an unprecedented rate.”

The 2021 Western North America heatwave was a rare and unprecedented compound weather event, that broke century-old temperature records by as much as 9°F. While the WWA team received worldwide publicity for their rapid attribution claims blaming anthropogenic climate change, subsequent peer-reviewed analysis showed that the rare event was not made more probable by global warming.

7.7. Summary

There is an ongoing scientific debate around attribution methods, particularly in attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement.

There are two areas of substantive criticism of the IPCC assessment of the causes of the recent warming: inadequate assessment of natural climate variability, and inappropriate statistical methods.

Detection of extreme weather events is challenged by their rarity, requiring a long data set and a choice of region and spatial scale to evaluate their occurrence against the background of natural weather and climate variability.

The most robust attribution statements for an extreme event relate to an incremental change (e.g. a temperature change in degrees or percent change in rainfall). Statements related to return times, quantitative changes in event magnitude and frequency, and probability of the extremes are not accurate owing to an inadequate amount of data, and are made with low confidence. There is no evidence in a change of weather or climate regime patterns from increasing greenhouse gases that would amplify or dampen extreme weather events, beyond basic thermodynamic considerations.

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8. Extreme weather in the US and elsewhere

8.1. Introduction

Weather extremes, usually related to temperature and/or precipitation, can disrupt infrastructure and therefore endanger human health and wellbeing. The issue is not whether extremes occur, for they are intrinsic to the chaotic climate system. Rather, it is whether there are long-term (decadal scale) changes in the frequency or character of extremes (“detection”), as well as the extent to which such changes and the attendant changes in hazards are caused by anthropogenic emissions of greenhouse gases (“attribution”; e.g., IPCC AR6 Seneviratne et al. 2021).

It is naïve to assume that any recent unprecedented extreme event is caused by human influences on the climate. That assumption is wrong in two ways. First, climate is about the statistical properties of weather over decades, not single events. And second, there are only about 130 years of reliable observational records that can be analyzed statistically. That brief interval does not begin to contain all of the extreme events that the climate system can create on its own. Over geologic time the climate system has generated an (essentially) infinite variety of weather patterns and extremes that humans have never observed, and thus are absent from the databases used to determine extreme statistics.³ [see *Perils of short data records* below]. For that reason, attributing an extreme event unprecedented in the record requires assumptions about the magnitude of natural variations.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of *Long Term Persistence* (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2015). LTP has a formal mathematical definition but it can be thought of intuitively as the presence of natural variations with strong autocorrelation properties that result in cycle-like behavior on long time scales. The presence of LTP requires long records to accurately estimate variability. Analysis of records short relative to the LTP scale will tend to underestimate variability, therefore overstating the significance of apparent trends and underestimating the likelihood of extreme events (Cohn and Lins 2005).

A good example of LTP is the eight-century long record of the annual minimum height of the Nile River observed at Roda Island in Cairo shown below in Figure 8.1.1. Since human influences on the global climate were negligible before the 20th century, the century-scale variability of the thirty-year average is entirely natural; Egyptians of the seventh and eight centuries would have been incorrect to assume that the worsening drought during that time was the “new normal.”

³ For example, under the simplest statistical assumptions there is a 37 percent chance that a 100-year event is NOT present in a century-long record.

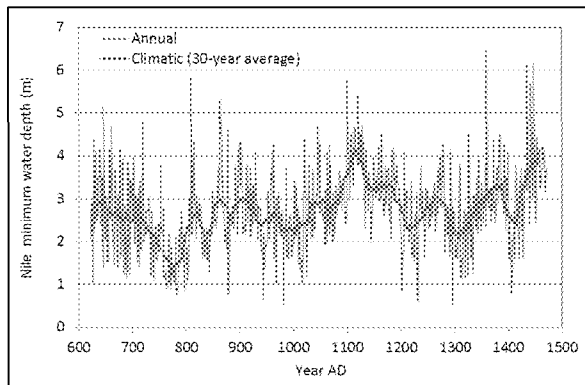


Figure 8.1.1: Nile River discharge [details, source]

With these caveats in mind we examine the evidence for changes in selected weather and climate extremes. It has become routine in media discussions, government and private sector discussions and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and climate change. Yet expert assessments have not typically drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing. For the benefit of readers who may not have read the relevant reports we will begin with extended excerpts of findings from previous IPCC and NCA assessments, then in the remainder of this chapter survey additional data relevant to US and global extreme weather trends.

8.2. Review of IPCC and NCA Findings on Extreme Weather

The sources we review will be denoted as follows:

SREX: The IPCC Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (2012)

AR5: The IPCC Fifth Assessment Report Working Group 1 (2013).

AR6: The IPCC Sixth Assessment Report Working Group 1 (2021).

NCA17: The US Climate Science Special Report of the Fourth National Climate Assessment (2017) Volume I Chapter 6.

8.2.1 Overview: IPCC Assessment of signal emergence in extreme weather types

(AR6 WG1 Table 12.12)

Climate Impact Driver Type	Climate Impact Driver Category	Already Emerged in the Historical Record?	Emerging by 2050 in Most Extreme CO2 Emissions Scenario?	Emerging by 2100 in Most Extreme CO2 Emissions Scenario?
Heat & Cold	Average air temperature	YES in most regions	YES	YES
	More heat extremes	YES in most regions	YES in land regions	YES
	Fewer cold extremes	YES in a few regions	YES in many regions	YES
	Less frost	NO	NO	NO
Wet & Dry	Average Precip. (Increase or Decrease)	NO	YES (incr) YES (decr)	YES (incr) YES (decr)
	River flooding	NO	NO	NO
	Heavy precip & pluvial flood	NO	NO	YES in a few regions
	Landslide	NO	NO	NO
	Aridity	NO	NO	NO
	Hydrologic Drought	NO	NO	NO
	Agricultural & ecological drought	NO	NO	NO
	Fire weather	NO	NO	NO
Wind	Average wind speed	NO	NO	NO
	Severe wind storm	NO	NO	NO
	Tropical cyclone	NO	NO	NO
	Sand and dust storm	NO	NO	NO
Snow and Ice	Snow, glacier & ice sheet	NO	YES in a few regions	YES Arctic snow
	Permafrost	YES	YES	YES
	Lake & river ice	NO	YES	YES
	Arctic sea ice	YES	YES	YES
	Antarctic sea ice	NO	YES	YES

	Heavy snowfall and ice storm	NO	NO	NO
	Hail	NO	NO	NO
	Snow avalanche	NO	NO	NO
Coastal	Relative sea level	NO	YES	YES
	Coastal flood	NO	NO	NO
	Coastal erosion	NO	NO	NO
Open Ocean	Average ocean temperature	YES	YES	YES
	Marine heat wave	NO	NO	NO
	Ocean acidity	NO	YES	YES
	Ocean salinity	YES	YES	YES
	Dissolved oxygen	YES (Pacific & S. Ocean)	YES	YES
Other	Air pollution weather	NO	NO	NO
	Solar or IR radiation at surface	NO	NO	NO

Table 8.2.1. IPCC AR6 summary of the probable emergence of an anthropogenic signal above natural climate variability for all global or regional “climate impact drivers” (CIDs) of concern for humans and ecosystems in response to increasing atmospheric greenhouse gas concentrations (primarily CO₂). Source: Table adapted from report of Working Group I, Table 12.12). Red = high confidence; yellow = medium confidence; green = no anthropogenic signal detectable above natural variability (50% confidence).

Table 8.2.1 reproduces the findings of AR6 Table 12.12 which indicates, for 34 major weather event and impact types, whether a signal of anthropogenic forcing has been detected in the historical record (column 1), whether such a signal is likely to emerge by 2050 under the extreme RCP8.5 scenario (column 2) and whether it is likely to emerge by 2100 under RCP8.5 forcing (column 3). It should be borne in mind that the latter two columns suffer from the deficiencies of GCMs discussed in Chapter XX. And as we discussed in Ch X on attribution, AR6 offers conflicting messages about attribution of extreme weather. Nevertheless, we provide this Table for reference.

Several patterns stand out. First, detection of an anthropogenic signal is asserted with *high confidence* in only four of the 34 weather impact categories, and with *medium confidence* in a further four. The IPCC

does NOT claim to have detected an anthropogenic signal in the remaining 26 categories. Of the four *high confidence* assertions, two are for changes in average temperatures (air and ocean), which are not measures of extreme weather. Further, two of the four *medium confidence* assertions are related to ocean chemistry and also not related to extreme weather. The IPCC does NOT assert a detectable human influence on many non-temperature weather features such as wind, precipitation, flooding, and drought.

Second, columns 2 and 3 show that the IPCC expects very few anthropogenic trends to emerge within this century, *even under the most extreme forcing scenario*. As we discuss in Section 4.2 the RCP8.5 scenario is an implausible high-end storyline, not a “base case” or “business-as-usual” projection. Even so, most weather impacts are not expected to show an anthropogenic signal this century. Natural variability dominates patterns of extreme weather systems and simplistic assertions of trend detection are frequently undermined by regional heterogeneity and trend reversals over time.

Taking wind as an example, the IPCC claims that an anthropogenic signal has NOT emerged in average wind speeds, severe windstorms, tropical cyclones, or sand and dust storms, and none are expected to emerge this century even under an extreme emissions scenario. The same applies to drought and fire weather. This table alone suffices to illustrate the gap between IPCC expert assessments of extreme weather and discussions in the popular media and political arenas. As we show below the Table reflects longstanding conclusions of the IPCC and other assessment bodies. In the next few sections we will simply present without comment excerpts from past assessment reports.⁴ In selecting these excerpts, we’ve focused on the highest-level summaries to avoid accusations of bias through “cherry picking”.

⁴ In these excerpts we have added **bold-face** emphasis, while *italicized* emphasis on confidence terms appears in the original sources. Citations in quoted text can be found in the underlying reports but are not reproduced here.

8.2.2 Flooding

SREX (p. 176)

In the United States and Canada during the 20th century and in the early 21st century, there is no compelling evidence for climate-driven changes in the magnitude or frequency of floods.

AR5 (p. 214)

AR4 WGI Chapter 3 (Trenberth et al., 2007) did not assess changes in floods but AR4 WGII concluded that **there was not a general global trend in the incidence of floods** (Kundzewicz et al., 2007). SREX went further to suggest that there was low agreement and thus *low confidence* at the global scale regarding changes in the magnitude or frequency of floods or even the sign of changes.

AR5 WGII assesses floods in regional detail accounting for the fact that trends in floods are strongly influenced by changes in river management (see also Section 2.5.2). Although the most evident flood trends appear to be in northern high latitudes, where observed warming trends have been largest, in some regions no evidence of a trend in extreme flooding has been found, for example, over Russia based on daily river discharge (Shiklomanov et al., 2007). Other studies for Europe (Hannaford and Marsh, 2008; Renard et al., 2008; Petrow and Merz, 2009; Stahl et al., 2010) and Asia (Jiang et al., 2008; Delgado et al., 2010) show evidence for upward, downward or no trend in the magnitude and frequency of floods, so that there is currently no clear and widespread evidence for observed changes in flooding except for the earlier spring flow in snow-dominated regions (Seneviratne et al., 2012).

In summary, there continues to be a lack of evidence and thus *low confidence* regarding the sign of trend in the magnitude and/or frequency of floods on a global scale.

AR6 (Ch 11 p. 1568)

The SREX (Seneviratne et al., 2012) assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report (Hartmann et al., 2013). The SR15 (Hoegh-Guldberg et al., 2018) found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. **While the number of studies on flood trends has increased since the AR5 report, and there were also new analyses after the release of SR15 (Berghuijs et al., 2017; Blöschl et al., 2019; Gudmundsson et al., 2019), hydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.**

In summary, the seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). **Confidence about peak flow trends over past decades on the global scale is *low*, but there are regions experiencing increases**, including parts of Asia,

southern South America, the northeast USA, northwestern Europe, and the Amazon, **and regions experiencing decreases**, including parts of the Mediterranean, Australia, Africa, and the southwestern USA.

US NCA17 pp. 240-41:

“The IPCC AR5 did not attribute changes in flooding to anthropogenic influence nor report detectable changes in flooding magnitude, duration, or frequency. Trends in extreme high values of streamflow are mixed across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude but does not provide robust evidence that these trends are attributable to human influences...

The complex mix of processes complicates the formal attribution of observed flooding trends to anthropogenic climate change and suggests that additional scientific rigor is needed in flood attribution studies. As noted above, precipitation increases have been found to strongly influence changes in flood statistics. However, in U.S. regions, **no formal attribution of precipitation changes to anthropogenic forcing has been made so far, so indirect attribution of flooding changes is not possible. Hence, no formal attribution of observed flooding changes to anthropogenic forcing has been claimed.**”

8.2.3 Heatwaves

AR5 (p. 212 WG1)

Table 2.13 shows that there has been a *likely* increasing trend in the frequency of heatwaves since the middle of the 20th century in Europe and Australia and across much of Asia where there are sufficient data. However, confidence on a global scale is *medium* owing to lack of studies over Africa and South America but also in part owing to differences in trends depending on how heatwaves are defined (Perkins et al., 2012). Using monthly means as a proxy for heatwaves Coumou et al. (2013) and Hansen et al. (2012) indicate that record-breaking temperatures in recent decades substantially exceed what would be expected by chance but caution is required when making inferences between these studies and those that deal with multi-day events and/ or use more complex definitions for heatwave events. **There is also evidence in some regions that periods prior to the 1950s had more heatwaves (e.g., over the USA, the decade of the 1930s stands out and is also associated with extreme drought conditions** (Peterson et al., 2013) whereas conversely in other regions heatwave trends may have been underestimated owing to poor quality and/or consistency of data (e.g., Della-Marta et al. (2007a) over Western Europe; Kuglitsch et al. (2009, 2010) over the Mediterranean). Recent available studies also suggest that the number of cold spells has reduced significantly since the 1950s (Donat et al., 2013a, 2013c).

In summary, new analyses continue to support the AR4 and SREX conclusions that since about 1950 it is *very likely* that the numbers of cold days and nights have decreased and the numbers of warm days and

nights have increased overall on the global scale, that is, for land areas with sufficient data. It is *likely* that such changes have also occurred across most of North America, Europe, Asia and Australia.

NCA17 (pp. 190-191)

Changes in warm extremes are more nuanced than changes in cold extremes. For instance, the warmest daily temperature of the year increased in some parts of the West over the past century (Figure 6.3), but there were decreases in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net decrease (Table 6.2), most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]). The decreases in the eastern half of [the] Nation, particularly in the Great Plains, are mainly tied to the unprecedented summer heat of the 1930s Dust Bowl era, which was exacerbated by land-surface feedbacks driven by springtime precipitation deficits and land mismanagement. However, anthropogenic aerosol forcing may also have reduced summer temperatures in the Northeast and Southeast from the early 1950s to the mid-1970s, and agricultural intensification may have suppressed the hottest extremes in the Midwest.

Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). **Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter (Figure 6.4). As with warm daily temperatures, heat wave magnitude reached a maximum in the 1930s.**

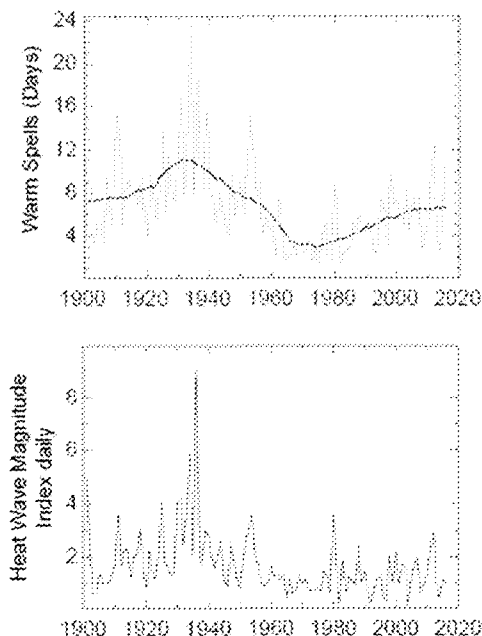


Figure 8.2.1: US Heat waves since 1900. Source: NCA17 Figure 6.4

AR6 (p. 1550)

In North America (Table 11.19), there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, **while there are more contrasting trends in the annual maximum daily temperatures** in parts of the USA (Figure 11.9; Lee et al., 2014; van Oldenborgh et al., 2019; Dunn et al., 2020).

8.2.4 Extreme snowfall events

Note: extreme snowfall events in the US northeast are assessed in relation to winter Extratropical Cyclone (ETC) activity.

AR6 Ch 11. p. 1593

There is *high confidence* that snowfall associated with winter ETCs will decrease in the future, because increases in tropospheric temperatures lead to a lower proportion of precipitation falling as snow (O’Gorman, 2014; Rhoades et al., 2018; Zarzycki, 2018). However, there is *medium confidence* that extreme snowfall events associated with winter ETCs will change little in regions where snowfall will be supported in the future (O’Gorman, 2014; Zarzycki, 2018).

8.2.5 Extreme precipitation

SREX (p. 142)

Recent studies have updated the assessment of the AR4, with more regional results now available (Table 3-2). Overall, this additional evidence confirms that **more locations and studies show an increase than a decrease in extreme precipitation, but that there are also wide regional and seasonal variations**, and trends in many regions are not statistically significant (Table 3-2)... Based on station data from Canada, the United States, and Mexico, Peterson et al. (2008a) reported that heavy precipitation has been increasing over 1950-2004, as well as the average amount of precipitation falling on days with precipitation.

AR5 (pp. 213-14)

In summary, further analyses continue to support the AR4 and SREX conclusions that it is *likely* that since 1951 there have been statistically significant increases in the number of heavy precipitation events (e.g., above the 95th percentile) in more regions than there have been statistically significant decreases, but

there are strong regional and subregional variations in the trends. In particular, many regions present statistically non-significant or negative trends, and, where seasonal changes have been assessed, there are also variations between seasons (e.g., more consistent trends in winter than in summer in Europe). The overall most consistent trends towards heavier precipitation events are found in central North America (very likely increase) but assessment for Europe shows likely increases in more regions than decreases.

AR6 (p. 1560)

In North America, there is robust evidence that the magnitude and intensity of extreme precipitation has *very likely* increased since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 (Sun et al., 2020, also Figure 11.13). There is, however, regional diversity. In Canada, there is a lack of detectable trends in observed annual maximum daily (or shorter duration) precipitation (Shephard et al., 2014; Mekis et al., 2015; Vincent et al., 2018).

NCA17 pp. 213-14:

Detectability of trends (compared to internal variability) for a number of precipitation metrics over the continental United States has been examined; **however, trends identified for the U.S. regions have not been clearly attributed to anthropogenic forcing.** One study concluded that increasing precipitation trends in some north-central U.S. regions and the extreme annual anomalies there in 2013 were at least partly attributable to the combination of anthropogenic and natural forcing... **Based on current evidence, it is concluded that detectable but not attributable increases in mean precipitation have occurred over parts of the central United States.** Formal detection-attribution studies indicate a human contribution to extreme precipitation increases over the continental United States, but confidence is *low* based on those studies alone due to the short observational period, high natural variability, and model uncertainty.

In summary, based on available studies, it is concluded that for the continental United States there is *high confidence* in the detection of extreme precipitation increases, while there is *low confidence* in attributing the extreme precipitation changes purely to anthropogenic forcing.

8.2.6 Tornadoes and severe convective storms

IPCC AR6 Sct. 11.7.3, p. 1594

Severe convective storms are convective systems that are associated with extreme phenomena such as tornadoes, hail, heavy precipitation (rain or snow), strong winds, and lightning.

The assessment of changes in severe convective storms in SREX (Chapter 3, Seneviratne et al., 2012) and AR5 (Chapter 12, Collins et al., 2013) is limited and focused mainly on tornadoes and hail storms. The

SREX assessed that **there is low confidence in observed trends in tornadoes and hail** because of data inhomogeneities and inadequacies in monitoring systems. Subsequent literature assessed in the Climate Science Special Report (Kossin et al., 2017) led to the assessment of the observed tornado activity over the 2000s in the USA, with a decrease in the number of days per year with tornadoes and an increase in the number of tornadoes on these days (*medium confidence*). However, **there is low confidence in past trends for hail and severe thunderstorm winds**. Climate models consistently project environmental changes that would support an increase in the frequency and intensity of severe thunderstorms that combine tornadoes, hail, and winds (*high confidence*), but there is *low confidence* in the details of the projected increase.

... In summary, because the definition of severe convective storms varies depending on the literature and the region, it is not straightforward to make a synthesizing view of observed trends in severe convective storms in different regions. In particular, **observational trends in tornadoes, hail, and lightning associated with severe convective storms are not robustly detected** due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant, but their variability of occurrence has increased since the 1970s, particularly over the 2000s, with **a decrease in the number of days per year, and an increase in the number of tornadoes on these days** (*high confidence*). Detected tornadoes have also increased in Europe, but the trend depends on the density of observations.

... In summary, **it is extremely difficult to detect and attribute changes in severe convective storms**. There is limited evidence that extreme precipitation associated with severe convective storms has increased in some cases.

8.2.7 Hurricanes and Tropical Cyclones

SREX (p. 159):

There have been no significant trends observed in global tropical cyclone frequency records, including over the present 40-year period of satellite observations (e.g., Webster et al., 2005). Regional trends in tropical cyclone frequency have been identified in the North Atlantic, but the fidelity of these trends is debated (Holland and Webster, 2007; Landsea, 2007; Mann et al., 2007a). Different methods for estimating undercounts in the earlier part of the North Atlantic tropical cyclone record provide mixed conclusions (Chang and Guo, 2007; Mann et al., 2007b; Kunkel et al., 2008; Vecchi and Knutson, 2008). Regional trends have not been detected in other oceans (Chan and Xu, 2009; Kubota and Chan, 2009; Callaghan and Power, 2011). It thus remains uncertain whether any observed increases in tropical cyclone frequency on time scales longer than about 40 years are robust, after accounting for past changes in observing capabilities (Knutson et al., 2010).

AR5 (pp. 216-17):

Current data sets indicate no significant observed trends in global tropical cyclone frequency over the past century and it remains uncertain whether any reported long-term increases in tropical cyclone frequency are robust, after accounting for past changes in observing capabilities (Knutson et al., 2010). **No robust trends in annual numbers of tropical storms, hurricanes and major hurricanes counts have been identified** over the past 100 years in the North Atlantic basin. Measures of land-falling tropical cyclone frequency (Figure 2.34) are generally considered to be more reliable than counts of all storms which tend to be strongly influenced by those that are weak and/or short lived. Callaghan and Power (2011) find a statistically significant decrease in Eastern Australia land-falling tropical cyclones since the late 19th century although including 2010/2011 season data this trend becomes non-significant (i.e., a trend of zero lies just inside the 90% confidence interval). Significant trends are not found in other oceans on shorter time scales (Chan and Xu, 2009; Kubota and Chan, 2009; Mohapatra et al., 2011; Weinkle et al., 2012), although Grinsted et al. (2012) find a significant positive trend in eastern USA using tide-gauge data from 1923–2008 as a proxy for storm surges associated with land-falling hurricanes. Differences between tropical cyclone studies highlight the challenges that still lie ahead in assessing long-term trends.

In summary, this assessment does not revise the SREX conclusion of *low confidence* that any reported long-term (centennial) increases in tropical cyclone activity are robust, after accounting for past changes in observing capabilities. More recent assessments indicate that **it is unlikely that annual numbers of tropical storms, hurricanes and major hurricanes counts have increased over the past 100 years in the North Atlantic basin**. Evidence, however, is for a virtually certain increase in the frequency and intensity of the strongest tropical cyclones since the 1970s in that region.

AR6 (p. 1585)

There is *low confidence* in most reported long-term (multidecadal to centennial) trends in TC frequency- or intensity-based metrics due to changes in the technology used to collect the best-track data. This should not be interpreted as implying that no physical (real) trends exist, but rather as indicating that either the quality or the temporal length of the data is not adequate to provide robust trend detection statements, particularly in the presence of multidecadal variability.

There are previous and ongoing efforts to homogenize the best-track data (Elsner et al., 2008; Kossin et al., 2013, 2020; Choy et al., 2015; Landsea, 2015; Emanuel et al., 2018) and there is substantial literature that finds positive trends in intensity-related metrics in the best-track during the “satellite period”, which is generally limited to the past ~40 years (Kang and Elsner, 2012; Kishtawal et al., 2012; Kossin et al., 2013, 2020; Mei and Xie, 2016; Zhao et al., 2018; Tauvale and Tsuboki, 2019). **When best-track trends are tested using homogenized data, the intensity trends generally remain positive, but are smaller in amplitude** (Kossin et al., 2013; Holland and Bruyère, 2014). **Kossin et al. (2020) extended the homogenized TC intensity record to the period 1979–2017 and identified significant global increases in major TC exceedance probability of about 6% per decade.**⁵ In addition to trends in TC intensity, there is

⁵ The **underlined** text referenced a study (Kossin et al. 2020) that later retracted a portion of its findings. Those authors assembled a data set on global TC incidence spanning 1979 to 2017 from which they claimed that the global fraction of TCs reaching major status (Cat 3–5) rose from 27% during 1979-1997

evidence that TC intensification rates and the frequency of rapid intensification events have increased within the satellite era (Kishtawal et al. 2012; Balaguru et al., 2018; Bhatia et al., 2018). The increase in intensification rates is found in the best-track as well as the homogenized intensity data.

A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows no trend in the frequency of U.S. landfall events (Knutson et al., 2019).

8.2.8 Droughts

US NCA17 REPORT (Ch. 8, Wehner et al. 2017)

p. 231:

Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the 1930s remains the benchmark drought and extreme heat event in the historical record (very high confidence). **While by some measures drought has decreased over much of the continental United States in association with long-term increases in precipitation, neither the precipitation increases nor inferred drought decreases have been confidently attributed to anthropogenic forcing.**

The human effect on recent major U.S. droughts is complicated. Little evidence is found for a human influence on observed precipitation deficits, but much evidence is found for a human influence on surface soil moisture deficits due to increased evapotranspiration caused by higher temperatures. (*High confidence*)

p. 233:

Drought is, of course, directly connected to seasonal precipitation totals. Figure 7.1 shows detectable observed recent changes in seasonal precipitation. In fact, the increases in observed summer and fall precipitation are at odds with the projections in Figure 7.5. **As a consequence of this increased precipitation, drought statistics over the entire CONUS have declined.**

to 31% during 1998-2017 and that the increase was statistically significant. However, closer examination of their results showed a significant increase only in the North Atlantic (18% to 34%) whereas changes in all other basins (Eastern Pacific, Western Pacific, North Indian, South Indian, South Pacific) were not statistically significant. In a subsequent correction (<https://www.pnas.org/doi/10.1073/pnas.2021573117>), Kossin et al. stated that the global probability of observing a major TC rose from 34% during 1979-1997 to 37% in the later period and that the evidence for statistical significance was now weaker. Nevertheless, the authors claimed that the correction did not affect their conclusions.

SREX (p. 170)

From a paleoclimate perspective recent droughts are not unprecedented, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia (Jansen et al., 2007). Recent studies extend this observation to African and Indian droughts (Sinha et al., 2007; Shanahan et al., 2009): much more severe and longer droughts occurred in the past centuries with widespread ecological, political, and socioeconomic consequences. Overall, these studies confirm that in the last millennium several extreme droughts have occurred (Breda and Badeau, 2008; Kallis, 2008; Büntgen et al., 2010).

In North America, there is *medium confidence* that there has been an overall slight tendency toward less dryness (wetting trend with more soil moisture and runoff; Table 3-2), although analyses for some subregions also indicate tendencies toward increasing dryness. This assessment is based on several lines of evidence, including simulations with different hydrological models as well as PDSI and CDD estimates (Alexander et al., 2006; Andreadis and Lettenmaier, 2006; van der Schrier et al., 2006a; Kunkel et al., 2008; Sheffield and Wood, 2008a; Dai, 2011).

The most severe droughts in the 20th century have occurred in the 1930s and 1950s, where the 1930s Dust Bowl was most intense and the 1950s drought most persistent (Andreadis et al., 2005) in the United States, while in Mexico the 1950s and late 1990s were the driest periods. Recent regional trends toward more severe drought conditions were identified over southern and western Canada, Alaska, and Mexico, with subregional exceptions (Dai, 2011).

SREX (p. 172)

Overall, though new studies have furthered the understanding of the mechanisms leading to drought, there is still relatively limited evidence to provide an attribution of observed changes, in particular given the issues associated with the availability of observational data (Section 3.2.1) and the definition and computation of drought indicators (Box 3-3). This latter point was mostly identified in post-AR4 studies (Box 3-3). Moreover, regions where consistent increases in drought are identified (see ‘Observed Changes’) are only partly consistent with those where projections indicate an enhancement of drought conditions in coming decades (see next paragraphs). We thus assess that there is *medium confidence* (see also Section 3.1.5) that anthropogenic influence has contributed to some changes in the drought patterns observed in the second half of the 20th century, based on its attributed impact on precipitation and temperature changes (though temperature can only be indirectly related to drought trends; see Box 3-3). However there is *low confidence* in the attribution of changes in droughts at the level of individual regions.

AR5 (pp. 214-215)

Based on evidence since AR4, SREX concluded that there were not enough direct observations of dryness to suggest high confidence in observed trends globally, although there was *medium confidence* that since the 1950s some regions of the world have experienced more intense and longer droughts. The

differences between AR4 and SREX are due primarily to analyses post-AR4, differences in how both assessments considered drought and updated IPCC uncertainty guidance.

Because drought is a complex variable and can at best be incompletely represented by commonly used drought indices, discrepancies in the interpretation of changes can result. For example, Sheffield and Wood (2008) found decreasing trends in the duration, intensity and severity of drought globally. Conversely, Dai (2011a,b) found a general global increase in drought, although with substantial regional variation and individual events dominating trend signatures in some regions (e.g., the 1970s prolonged Sahel drought and the 1930s drought in the USA and Canadian Prairies). Studies subsequent to these continue to provide somewhat different conclusions on trends in global droughts and/or dryness since the middle of the 20th century (Sheffield et al., 2012; Dai, 2013; Donat et al., 2013c; van der Schrier et al., 2013).

In summary, the current assessment concludes that there is not enough evidence at present to suggest more than *low confidence* in a global-scale observed trend in drought or dryness (lack of rainfall) since the middle of the 20th century, owing to lack of direct observations, geographical inconsistencies in the trends, and dependencies of inferred trends on the index choice. Based on updated studies, AR4 conclusions regarding global increasing trends in drought since the 1970s were probably overstated. However, it is *likely* that the frequency and intensity of drought has increased in the Mediterranean and West Africa and decreased in central North America and north-west Australia since 1950.

AR6 (Drought, Observed trends, Section 11.6.2, pp. 1573-75)

p. 1573

Strong precipitation deficits have been recorded in recent decades in the Amazon (2005, 2010), south-western China (2009–2010), south-western North America (2011–2014), Australia (1997–2009), California (2014), the middle East (2012–2016), Chile (2010–2015), the Great Horn of Africa (2011), among others (van Dijk et al., 2013; Mann and Gleick, 2015; Rowell et al., 2015; Marengo and Espinoza, 2016; Dai and Zhao, 2017; Garreaud et al., 2017, 2020; Marengo et al., 2017; Brito et al., 2018; Cook et al., 2018). **Global studies generally show no significant trends in SPI time series** (Orlowsky and Seneviratne, 2013; Spinoni et al., 2014), **and in derived drought frequency and severity data** (Spinoni et al., 2019), with very few regional exceptions (Section 11.9 and Figure 11.17).

p. 1574

For AR6 regions, several studies suggest an increase in the frequency and areal extent of soil moisture deficits, with examples in East Asia (Cheng et al., 2015; Y. Qin et al., 2015; Jia et al., 2018), Western and Central Europe (Trnka et al., 2015b), and the Mediterranean (Hanel et al., 2018; Moravec et al., 2019; Markonis et al., 2021). **Nonetheless, some analyses also show no long-term trends in soil drying in**

some AR6 regions – for example, in Eastern North America (Park Williams et al., 2017) and Central North America (Seager et al., 2019), as well as in North Eastern Africa (Kew et al., 2021).

There is evidence based on streamflow records of increased hydrological droughts in East Asia (D. Zhang et al., 2018) and southern Africa (Gudmundsson et al., 2019). **In areas of Western and Central Europe and Northern Europe, there is no evidence of changes in the severity of hydrological droughts since 1950** based on flow reconstructions (Caillouet et al., 2017; Barker et al., 2019) and observations (Vicente-Serrano et al., 2019). **In North America, depending on the methods, datasets and study periods, there are differences between studies that suggest an increase (Shukla et al., 2015; Udall and Overpeck, 2017) versus a decrease in hydrological drought frequency (Mo and Lettenmaier, 2018), but in general there is strong spatial variability** (Poshtiri and Pal, 2016). Streamflow observation reference networks of near-natural catchments have also been used to isolate the effect of climate trends on hydrological drought trends in a few regions, but these show limited trends in Northern Europe and Western and Central Europe (Stahl et al., 2010; Bard et al., 2015; Harrigan et al., 2018), North America (Dudley et al., 2020) and most of Australia, with the exception of Eastern and Southern Australia (X.S. Zhang et al., 2016).

p. 1575

Few AR6 regions show observed increases in meteorological drought (Section 11.9), mostly in Africa and South America (NES: *high confidence*; WAF, CAF, ESAF, SAM, SWS, SSA, SAS: *medium confidence*); a few others show a decrease (WSB, ESB, NAU, CAU, NEU, CNA: *medium confidence*). There are stronger signals indicating observed increases in agricultural and ecological drought (Section 11.9), which highlights the role of increased [evapotranspiration], driven by increased [Atmospheric Evaporative Demand], for these trends (Sections 11.6.2.3, 11.6.2.5). Past increases in agricultural and ecological droughts are found on all continents and several regions (WAF, CAF, WSAF, ESAF, WCA, ECA, EAS, SAU, MED, WCE, NES: *medium confidence*), while decreases are found only in one AR6 region (NAU: *medium confidence*). The more limited availability of datasets makes it more difficult to assess historical trends in hydrological drought at regional scale (Section 11.9). Increasing (MED: *high confidence*; WAF, EAS, SAU: *medium confidence*) and decreasing (NEU, SES: *medium confidence*) trends in hydrological droughts have only been observed in a few regions.

AR6 on Attribution (p. 1577)

There are only two AR6 regions in which there is at least *medium confidence* that human-induced climate change has contributed to changes in meteorological droughts (Section 11.9). In South-western South America (SSW), there is *medium confidence* that human-induced climate change has contributed to an increase in meteorological droughts (Boisier et al., 2016; Garreaud et al., 2020), while in Northern Europe (NEU), there is *medium confidence* that it has contributed to a decrease in meteorological droughts (Gudmundsson and Seneviratne, 2016) (Section 11.9). **In other AR6 regions, there is inconclusive evidence in the attribution of long-term trends, but a human contribution to single meteorological events or subregional trends has been identified in some instances... In North America,**

the human influence on precipitation deficits is complex (Wehner et al., 2017), with low confidence in the attribution of long-term changes in meteorological drought in AR6 regions.

8.3. Extreme weather trends at global and continental scale

8.3.1 Tropical Cyclones (TCs)

Hurricane strength records for the North Atlantic and the Western Pacific go back to 1950 and the record does not show an increase in either total or major TCs. Figure 8.3.1 was published by Roger Pielke Jr. as an update to the Best Track data series originally presented in Weinkle et al. (2012).

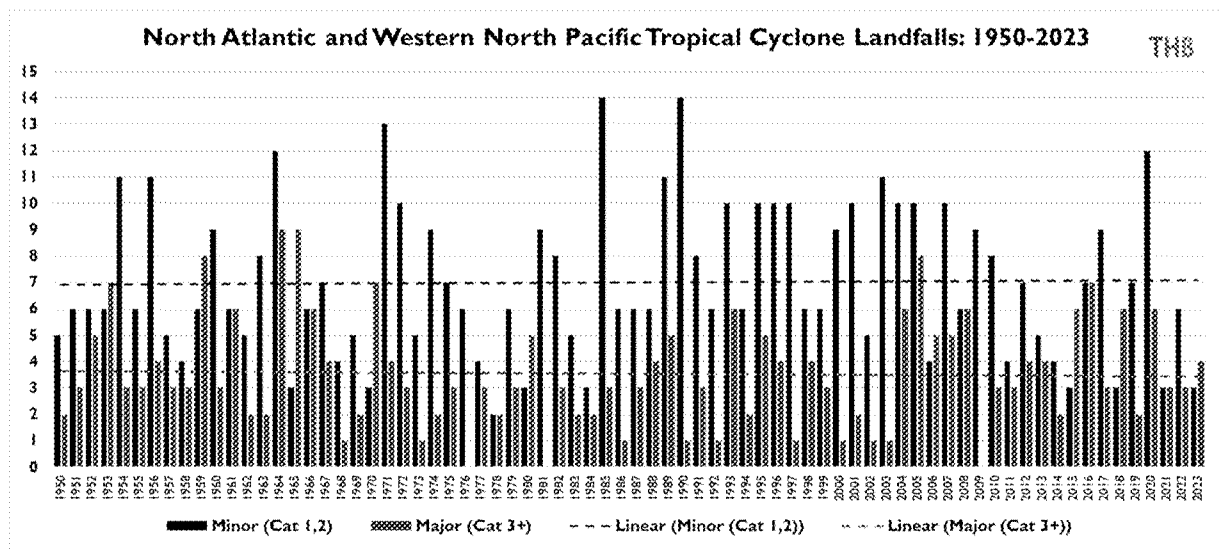


Figure 8.3.1. Tropical Cyclone Landfalls. Source: <https://rogerpielkejr.substack.com/p/global-tropical-cyclones>, Weinkle et al. (2012)

Similarly, Figure 8.3.2 (Maue 2025, <https://climatlas.com/tropical/>) shows that both all hurricanes and major hurricanes have not become more common since 1980, the period of rapidly growing human influences. In fact, both numbers have trended down slightly since the 1990s:

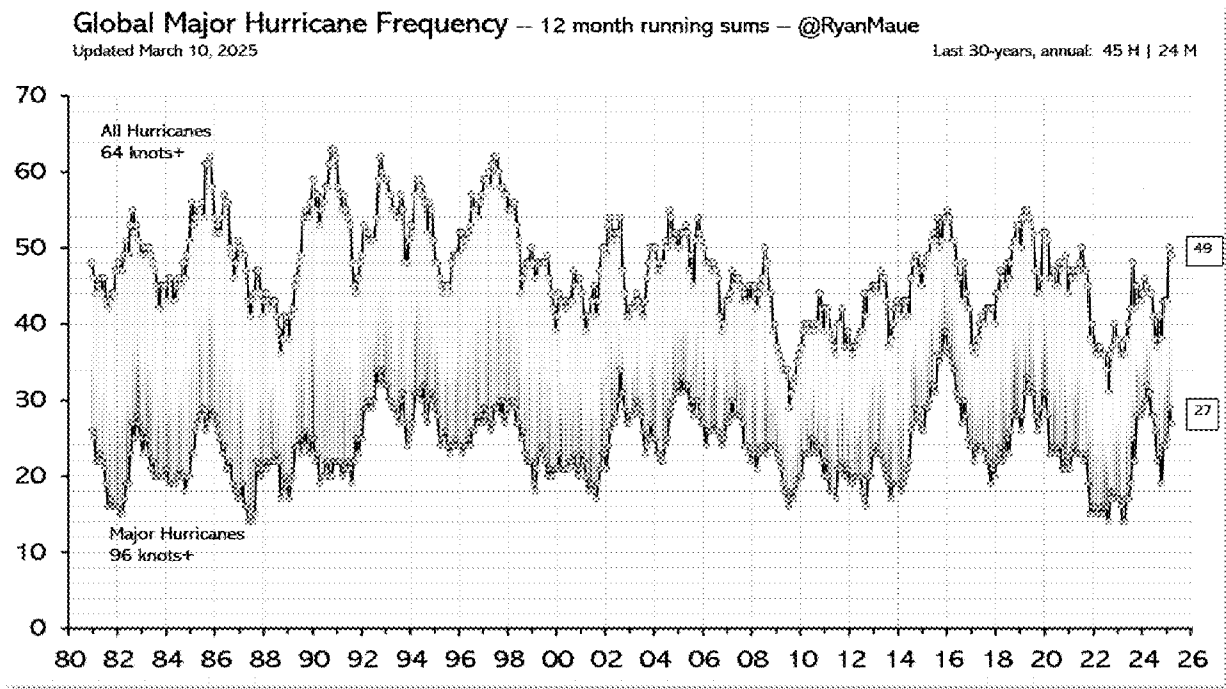


Figure 8.3.2: Global hurricane frequency. Source: Maue (2025)

A metric that combines the number, duration, and strength of TCs is the Accumulated Cyclone Energy (ACE) Index maintained at Colorado State University, shown in Figure 8.3.3. It clearly shows no long-term increase, in fact declining slightly since 1990.

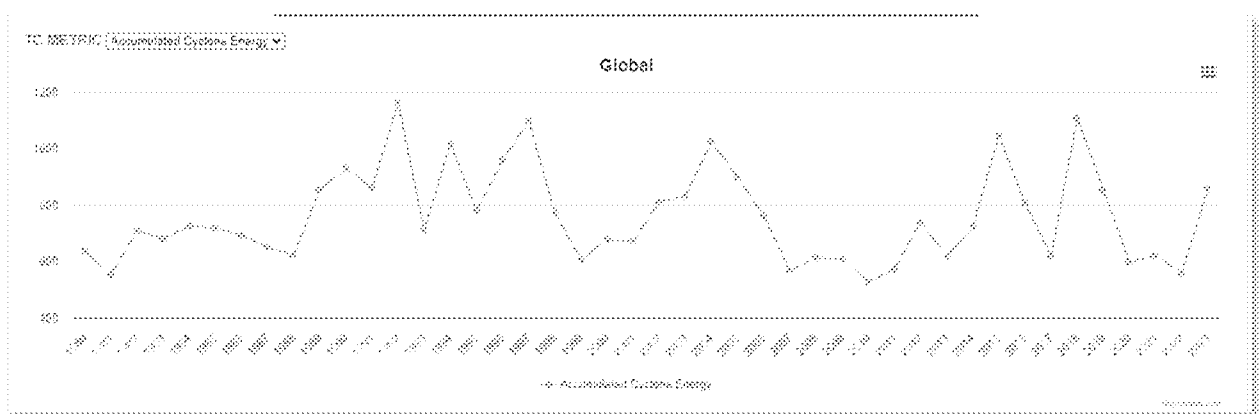


Figure 8.3.3: Global Accumulated Cyclone Energy. Source: Klotzbach (2025)

<https://tropical.atmos.colostate.edu/Realtime/index.php?arch&loc=global>

Note that Tu et al. (2024) report that the Power Dissipation Index (PDI), another different measure that combines hurricane number, duration, and strength, has either remained unchanged or has declined in all global oceanic basins since the mid-1990s.

Today's global climate simulations are too coarse to project changes in TCs directly. Rather, projections are derived from finer "downscaled" simulations or proxies involving sea surface temperatures, winds, and aerosols. By those methods, a warming climate is expected to show declining hurricane formation rates. (Chand et al. 2022). Climate models also project fewer Tropical Cyclones under future global warming, and even though models project they will increase in strength, the annual averages of rainfall maxima decline (Stansfield et al. 2020).

8.3.2 Wildfires

As shown in Figures 8.3.4 and 8.3.5 global wildfire activity as measured by European Space Agency peaked over a decade ago and shows a downward trend since.

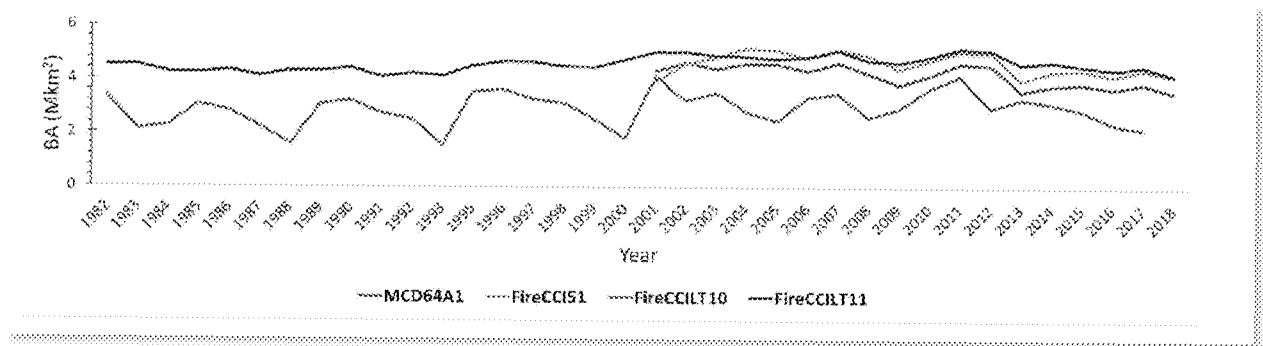


Figure 8.3.4: Global wildfire 1982-2018. Source: Copied from Oton et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used.



Figure 8.3.5: Global wildfire 2001-2018. Source: Copied from Lizundia-Loiola et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used

US data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 8.3.6.

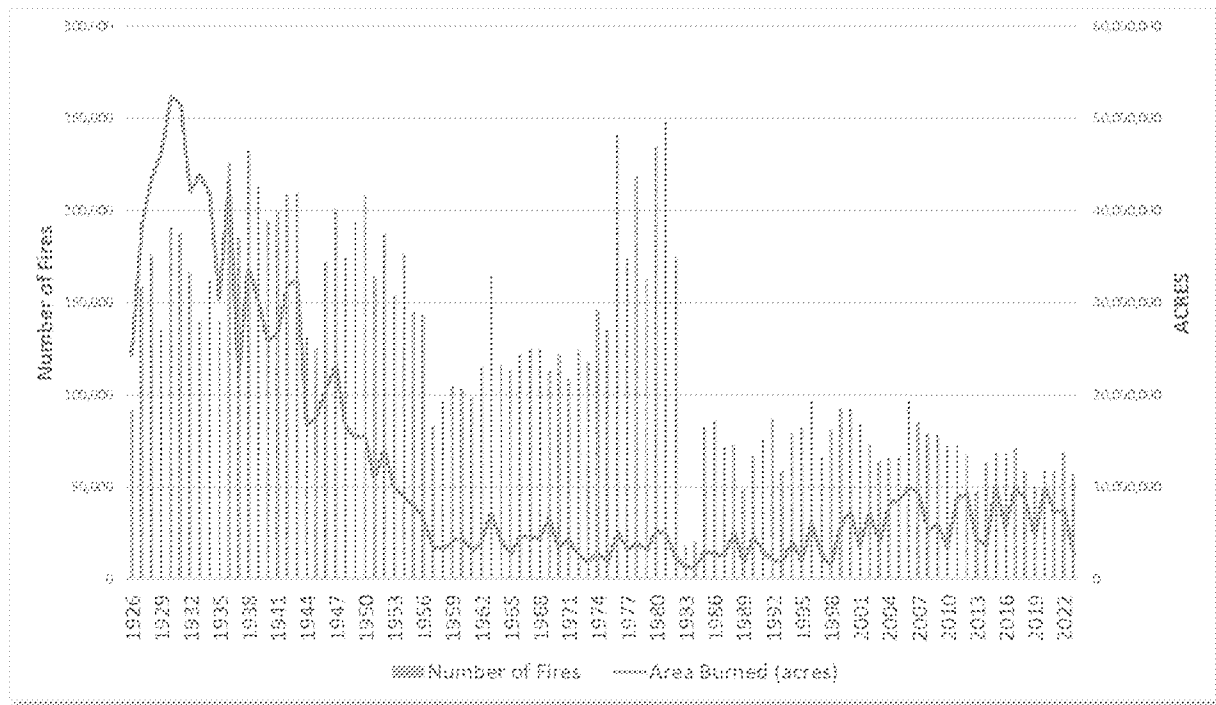


Figure 8.3.6: US wildfires 1926 to 2023. Source: National InterAgency Fire Centre data

Pre-2017 (archived)

https://web.archive.org/web/20200212033452/https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html. 2018-2023: <https://www.nifc.gov/fire-information/statistics/wildfires>

Note the NIFC has removed the pre-1960 data from its current website. They claim it is because measurement methods changed after 1960. This explanation seems inadequate since agencies blend temperature and extreme weather data series in other contexts when measurement systems changed. In this case if anything the measurement of wildfires has improved since the early 20th century so any bias will be towards understating early wildfire counts. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

It is difficult to establish a natural baseline for wildfire activity because of active fire suppression activity since 1900. Paleoclimatic evidence indicates, however, that past wildfire activity was much higher than at present. Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US for the past 1400 years. They also fit a model to predict expected fire activity as a function of climatic conditions. The results are summarized in Figure 8.3.7 below (from Figure 2 in their paper).

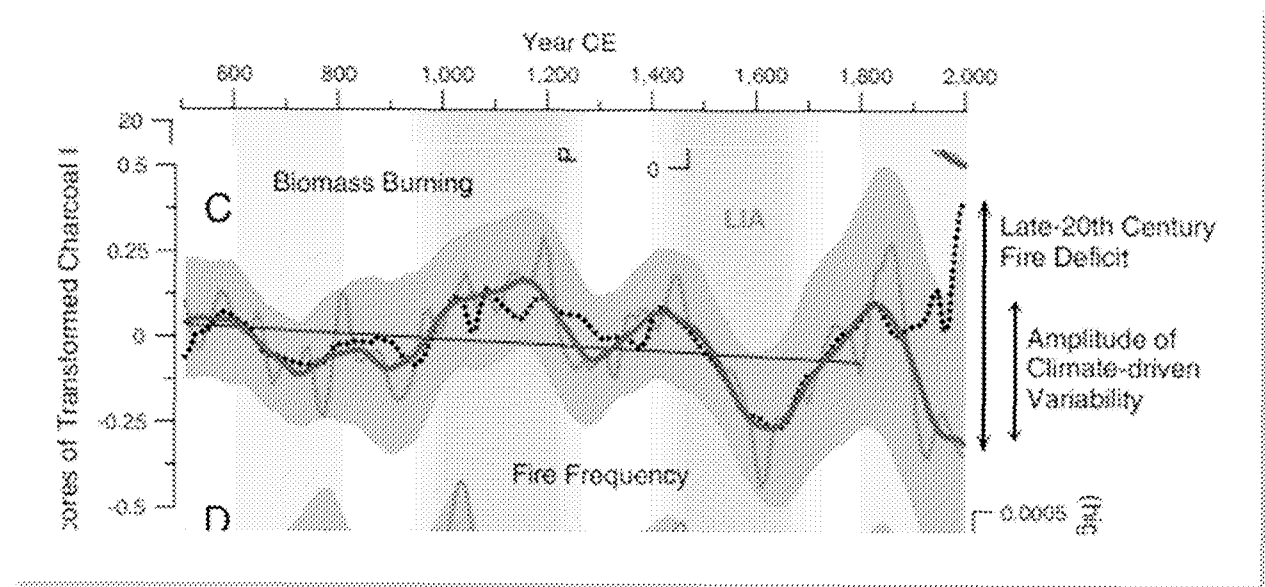


Figure 8.3.7: Fire frequency and fire deficit in the US. Source: Copied from Marlon et al. (2012)

In their figure the red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on the statistical model. The gap at the end implies there has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century it was less than what would have been observed in previous centuries based on the climatic conditions. Parks et al. (2025) likewise find that despite the recent increase in wildfire burn area in North America, a significant wildfire deficit remains relative to historical wildfire regimes.

8.3.3 Precipitation

Figure 8.3.8 shows that US long term data from NOAA shows an insignificantly increasing tendency toward extreme wetness (+0.001% per year)

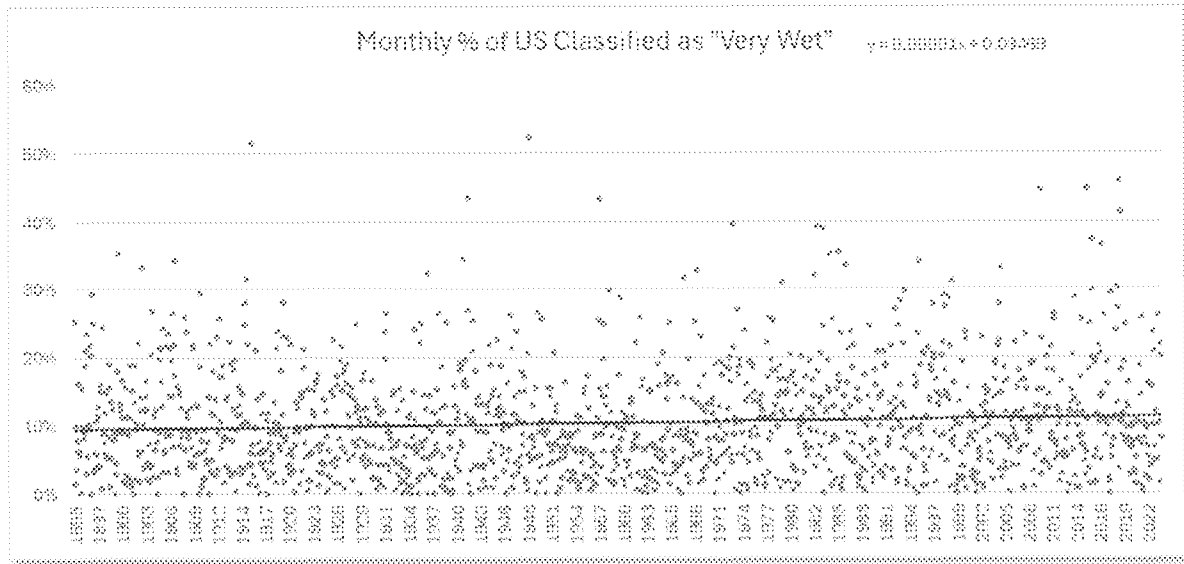


Figure 8.3.8: Long term US wetness (%). Source: NOAA

<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Precipitation will be discussed further in the review of CONUS data below.

8.3.4 Drought

As shown in Figure 8.3.9 US long term data (NOAA) shows an insignificantly declining tendency toward extreme dryness (-0.001% per year)

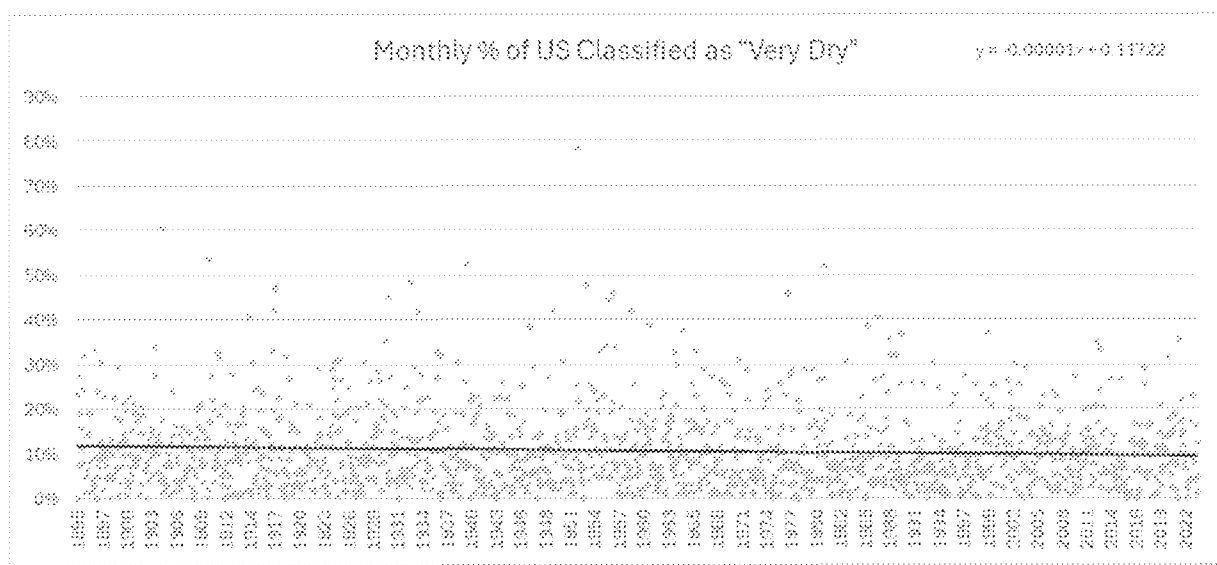


Figure 8.3.9: US dryness (%) 1895—2023. Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Kogan et al. (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: “it is possible to state firmly that global and main grain countries’ drought area and intensity trends have not been following global climate warming since 1980’s.”

8.4. Temperature and precipitation extremes in the Contiguous US (CONUS)

8.4.1 CONUS daily temperatures are becoming less extreme

Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although there are certainly errors in the dataset, with over 1,000 stations we can have relatively high confidence in any underlying signal that might be discovered.

We begin with the question of whether the occurrence of daily record high or low temperatures changed has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station and day, we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, the expected number of records for TMax would be 1.21 (=153/126) per station per year and for TMin 0.96 (=122/126) per station per year. Figure 8.4.1 indicates the observed distribution in time of the occurrence of these extreme events.

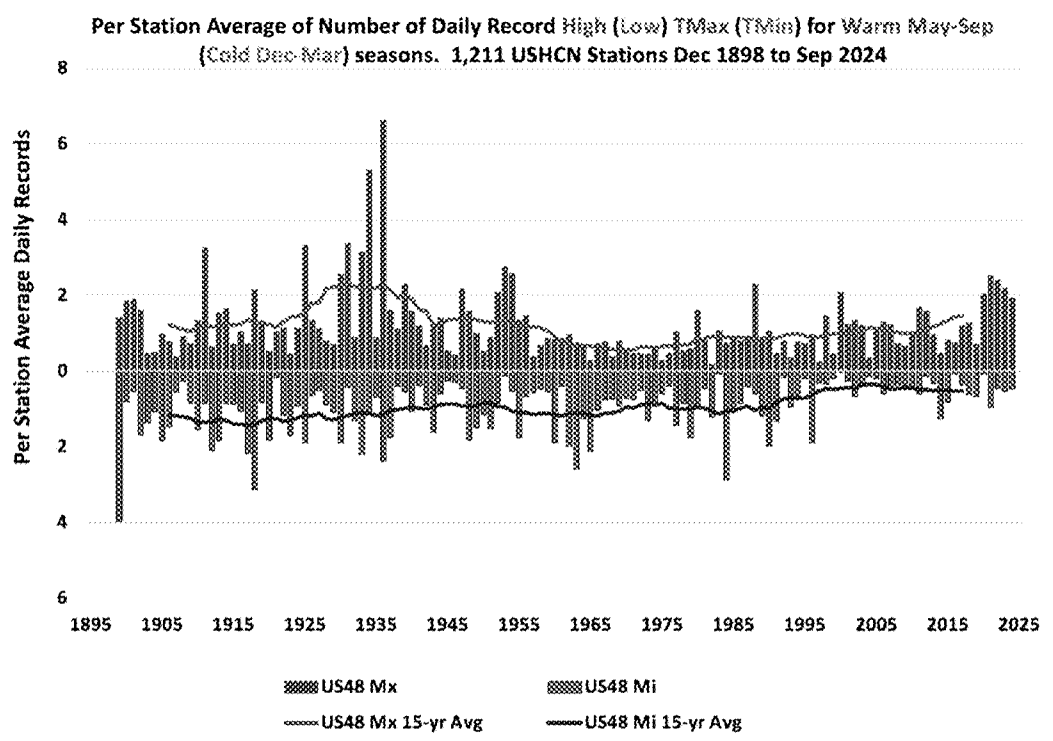


Figure 8.4.1 Number of daily record High (red) and Low (blue) for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

The results indicate a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. On a per-station average, 60% of the TMax records and 59% of the TMin records occurred in the first half of the period (1899-1961).

On the cold side, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 2nd. The frequency of cold records has declined, especially over the last quarter of the period in which only 13% of the extreme cold events were measured. In contrast, 25% of the extreme TMax records were achieved in the last quarter in accordance with statistical expectations. These general features have been noted in past assessments (IPCC AR5, IPCC AR6, NCA4, NCA5). Combining the two records the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 8.4.2. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated and converted to anomalies relative to the station's long term warm and cold season (respectively) averages. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 8.11 shows the 15-year trailing average of this measure which has clearly declined over the past century.

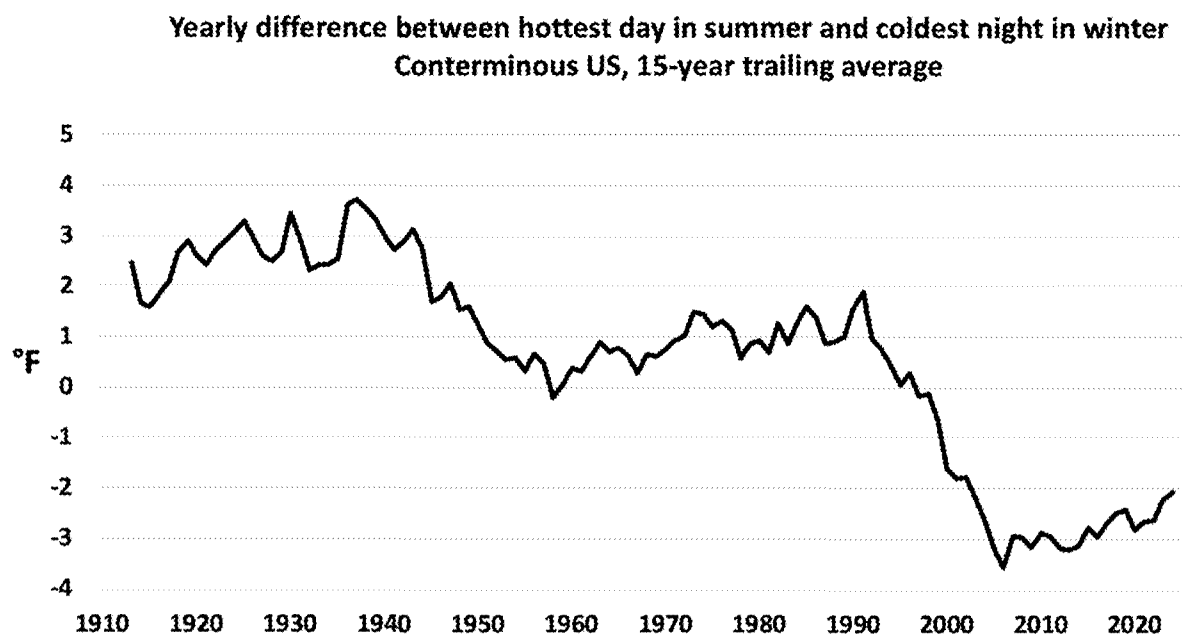


Figure 8.4.2. 15-year trailing average of the difference each year of each station's hottest warm-season TMax and coldest cold-season TMin relative to the long-term average.

The average difference for each station between the hottest summer TMax and coldest winter TMin has declined about 5°F in the past 126 years. The decline is due mostly to warming winter TMin, but a decline in the magnitude of summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (Spencer et al. 2025).

Summarizing Figures 8.4.1 and 8.4.2, while temperature extremes are regularly experienced in the US and attract a great deal of media attention, long term records show the US climate has become less extreme over time (milder) when measured in terms of the range between warm season maxima and cold season minima.

8.4.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent US National Climate Assessment report (NCA5) notes the increase in a threshold metric of number of days at or above 95°F, stating,

“The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021.”

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations that have near 95°F TMax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not impact the results much at all. In the past 126 years, the average CONUS station experienced 129 days exceeding 95°F per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, one needs to view such threshold analyses with caution.

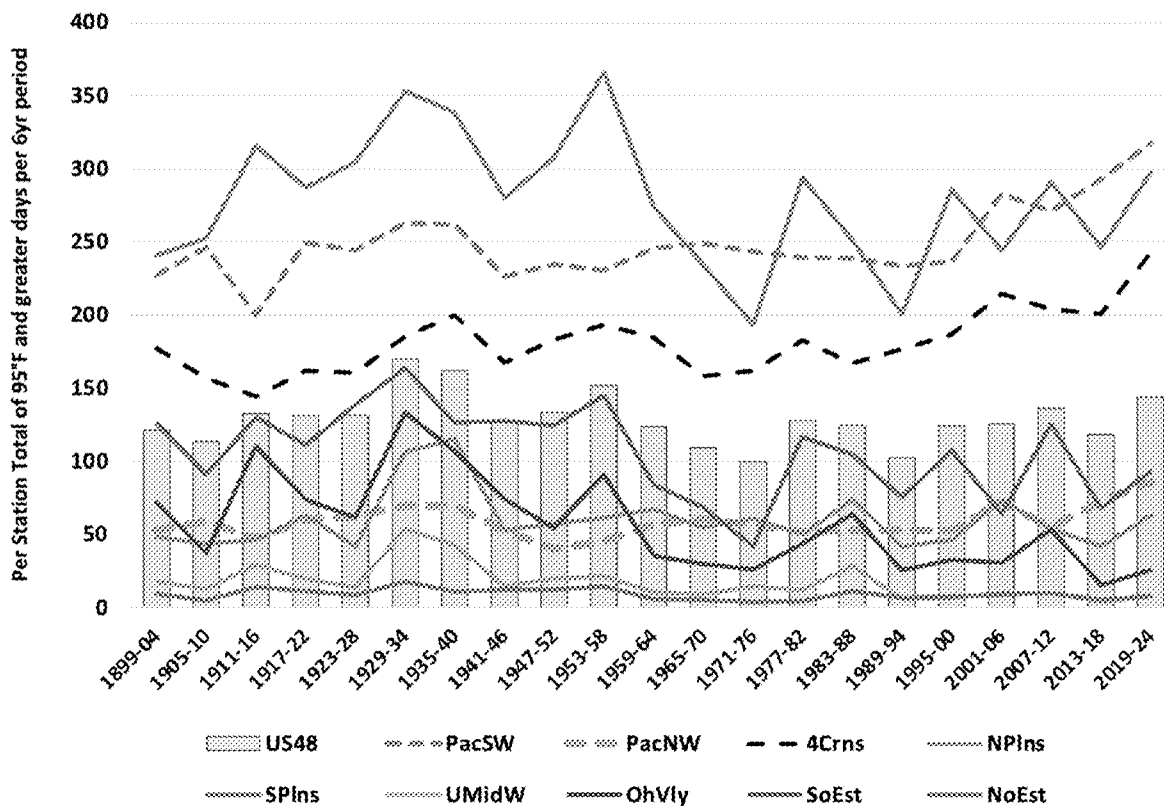


Figure 8.4.3. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, US 48 (bars) and regions (lines).

In Fig. 8.4.3 we see that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 is referenced as of the NCA5 claim, an event we examine more closely in Section 6.4. The evidence indicates it was a “black swan” event; *i.e.*, a single, unprecedented event in the record, not part of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW during that event was +10.8 C, the most extreme NH grid point summer anomaly in the 46 years from over 4 million grids. In contrast, the global anomaly during that time was virtually zero (+0.03 C, Mass et al. 2024).

The heading “The Risk of Temperature Extremes is Changing” suggests positive trends are now being observed in threshold temperatures on a widespread basis, but that is not evidenced in the combined CONUS results of the figures above.

8.4.3 Heatwaves

Heatwaves (consecutive days that exceed an extreme threshold) have a greater societal impact than a single daily record. We measure “Heatwave Days” here as the count of all days in May-Sep each year that exceed the 90th percentile and that lie within a run of at least six consecutive days. This is equivalent to the method used in NCA5 except that the reference period here is the entire record 1899-2024 while NCA5 truncated the reference period to 1961-1990, a cool time. That truncation boosts positive results (days exceeding the 90th percentile) in periods warmer than the reference period, especially starting in 1960 and moving to the present (see *Urban Influences* below).

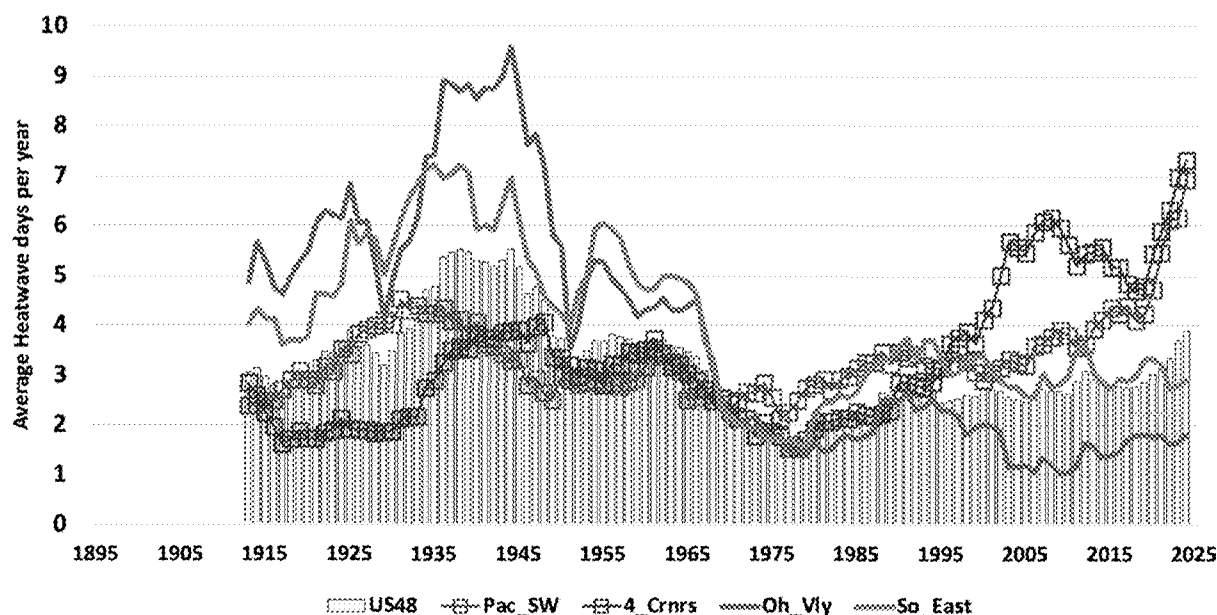


Figure 8.4.4 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (purple squares, CA, NV), 4_Crnrs (red squares, AZ,NM,UT,CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure 8.4.4 indicates again the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, as seen in the regional values for the Ohio Valley and the Southeast as examples. The West has seen a recent increase of heatwave days and the two regions with the highest number are shown, the Pacific Southwest and the Four-Corners (NCA5). This indicates that

the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West. For CONUS as a whole, heatwaves are no more common today than they were a century ago.

Of interest here is the regional variation of this metric. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per 15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

Urban influences

The NCA5 directs readers to the website <https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view the number of urban heatwaves by decade from the 1960s. The figure shows a monotonic increase in each decade from 2 occurrences per year in the 1960s to 6 in the 2020s. The definition of a heatwave is an unusual but practical measure of human discomfort - a period of at least 2 consecutive days when the minimum apparent temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest U.S. cities.

These increasing values since 1960 presented in USGCRP (2023) are entirely reasonable, but are unrelated to GHG emissions for at least two reasons. Urbanization in these cities is a major factor in the rise of TMin relative to co-located TMax and relative to TMin at rural stations. Also, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. This does not dismiss the real rise in nighttime temperatures in major U. S. cities and the societal impacts associated with these changes. However, we note for a variety of reasons, that summer TMax (especially in rural areas) serves as better response variable for detecting potential changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves.

8.4.4 Extremes in daily precipitation.

Because precipitation involves a discrete phase change (water vapor to liquid), it is stochastic and episodic in character and requires careful statistical treatment to understand variability over long time periods (see *8.1 Introduction*). The US National Climate Assessments (NCA4, NCA5) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme events are in the Northeast and the smallest in the West, a trend counter to the changes in temperature extremes.

McKittrick and Christy (2019) examined long-term and consistent station observations of daily precipitation to test some of these NCA claims for the Southeast and West Coast. When the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978), there were no significant trends for either region. For this report we updated these findings with similarly constructed observations from 29 stations on the Pacific Coast (1893ff from San Diego CA to Blaine WA), 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), and 21 stations in the Northeast (1888ff from Buffalo NY to Gardiner ME). The results were as follows.

Pacific region:

- Average precipitation trend is significant (downwards) in Astoria, insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Big Sur, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Aberdeen and Big Sur and negative and significant in Newport (insignificant elsewhere).
- Averaged over all stations in the region none of these three trend parameters is statistically significant.

Southeast region:

- The trend in average precipitation is positive and significant in Mobile and Quitman, insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Mobile, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Vicksburg and Norfolk, insignificant elsewhere.
- Averaged over all stations in the region none of these three trend parameters is statistically significant

Northeast region:

- The trend in average precipitation is positive and significant in 9 of 21 locations and in the region averaged overall.
- The trend in rainfall variance is positive and significant in Portland, Albany and Buffalo, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Portland and Gardiner, insignificant elsewhere.
- Averaged over all stations in the region the trend parameters for variance and maximum precipitation are not statistically significant.

Pacific Coast heavy rainfall events

The Pacific Coast receives considerable precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov et al. 2017, Pan et al. 2024). The worst-known such event in recent history was the ArkStorm that occurred between December 1861 and January 1862, which dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter et al. 2011).

SIDEBAR: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 8.2.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023
14-day	12.62	2023

	30-day	18.93	1998
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Table 8.2: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent data. 2023 appears to be an exceptional year and since it is near the end of the sample it might suggest that the climate has shifted into a more hazardous state, perhaps as a result of human influences.

But the picture is very different if we use a sample that begins 45 years earlier, in 1850. Table 8.3 shows that the record-setting events then all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th. Also, comparing the records of the two charts the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 8.3: Extreme rainfall records, San Francisco, 1850-2024.

The range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter et al. (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ArkStorm that struck the region. Evidently such extreme events have impacted the region about every 300 years, though not since 1895.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (see 6.4). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50% determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur. An important lesson is that the climate can deliver great surprises on its own, even without human influences.

We examine occurrences of 5-day deluges as follows. In a 130-year span there are 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values. A single year may have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation then the total number of these events across all stations should be evenly spread out over the years. In Fig. 8.4.5 we show the distribution in time of these events. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of these types of precipitation metrics, there is no indication of a tendency to become more frequent over time.

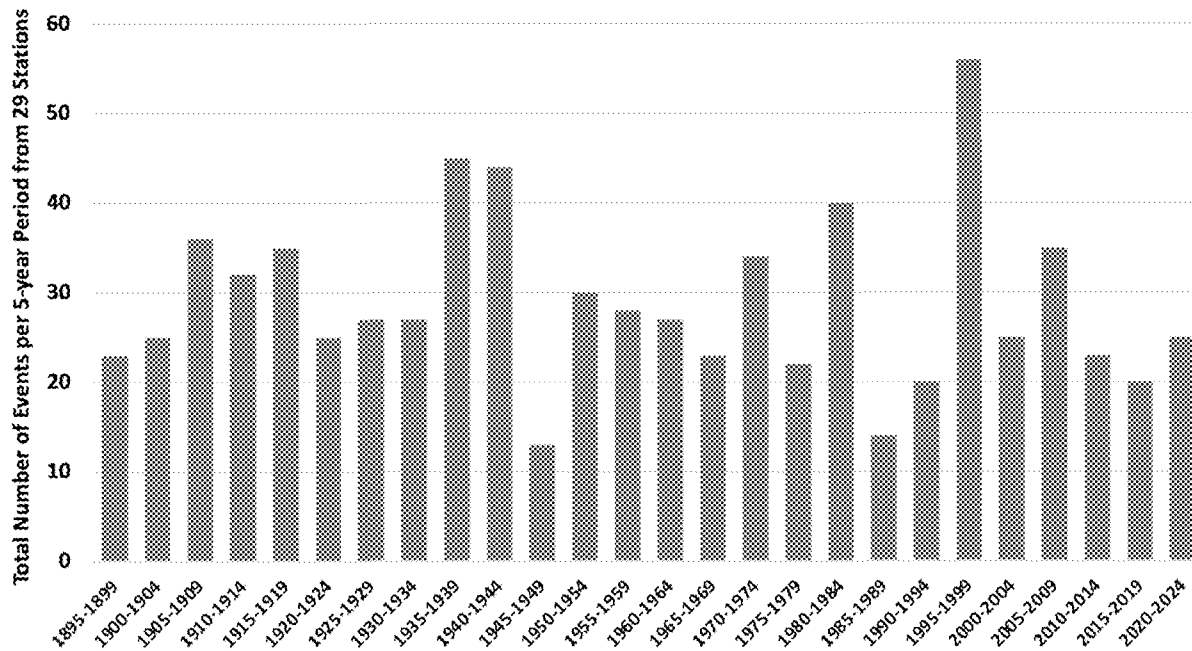


Figure 8.4.5. The time distribution by 5-year periods of the 26 heaviest occurrences for each station (i.e., nominal 1-in-5 year event).

Southeast heavy rainfall events

The temporal pattern of 5-day totals of the 1-in-5yr heavy events in the humid Southeast (Figure 8.4.6) is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 of a tendency for an increasing frequency of heavy events, due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

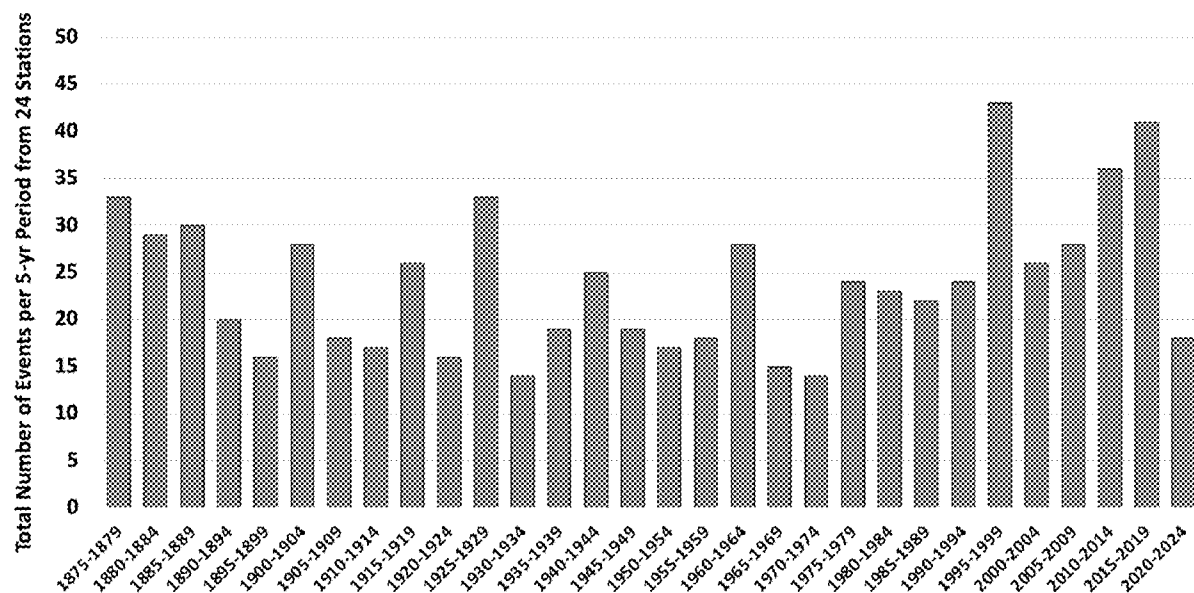


Figure 8.4.6. As above but for the 30 heaviest 1-in-5yr events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

Northwest heavy rainfall events

Fig. 8.4.7 shows the 27 (1-in-5yr) heaviest 3-day events for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest variations in time. In this region, 72% of the events occur during June to October and are dominated by tropical incursions of hurricanes, tropical storms or tropical storms that transition to extratropical systems. According to NCA4 and NCA5 this region experienced the largest increases in extreme events, so it shall be examined more closely.

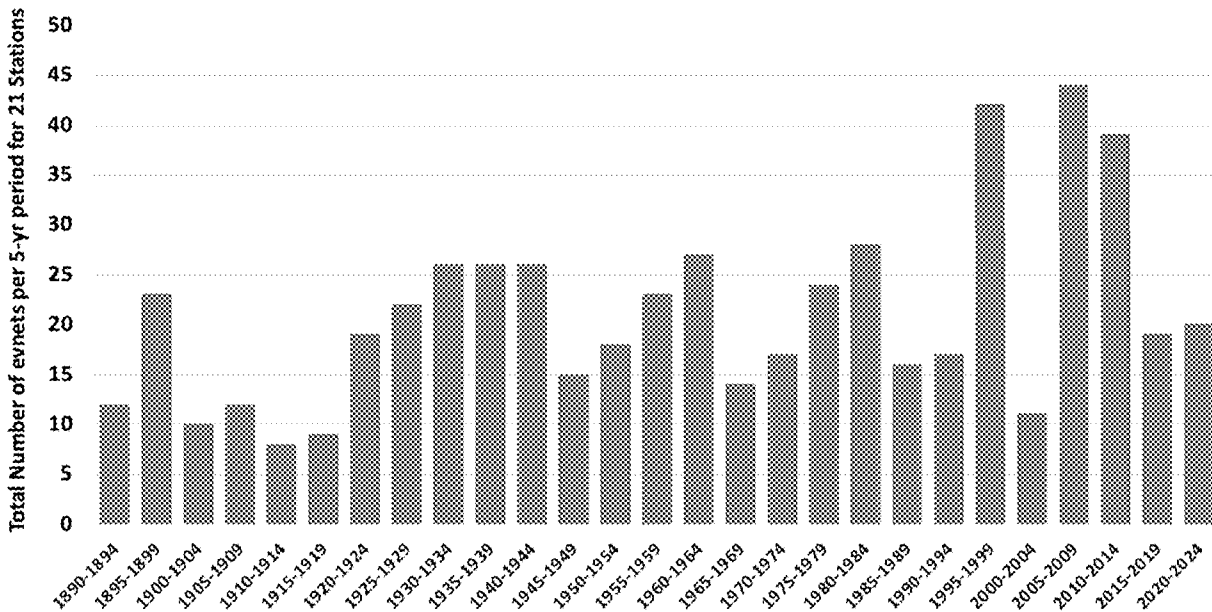


Figure 8.4.7. Time distribution of the heaviest 27 (1-in-5yr) heaviest 3-day precipitation events for 21 stations from NY to ME, including Montreal.

Howarth et al. (2019) report differences in the Northeast between two 18-year periods: 1979-96 and 1997-2014 (a similar region as in Fig. 8.16 that includes PA and NJ) of various precipitation extremes. One metric which indicated a dramatic increase (317%) was found for 24-hr events > 6 inches. This high increase is due to the very small numbers of such events of which there were only 6 in the first period and 25 in the second as reported for 58 stations. This high percentage increase is due to the very small numbers of the events; only 6 in the first period and 25 in the second. Most of the stations, did not record such an event suggesting these erratic, episodic events over brief, 18-yr periods, need scrutiny by additional statistical methods.

Using the information in Fig. 8.4.7 over the same years as Howarth et al. we find a 51% increase in the frequency of heavy events between the two periods. One can see in Fig. 8.16 that it was unfortunate that Howarth et al. ended in 2014 prior to a return to the long-term average of such events.

A feature of Howarth et al. is the use of single day totals which is questionable because extreme events are often spread across the time-of-observation boundary. Thus stations measuring at 0700 LT versus those at Midnight will have differing results for a particular event which would then have major impacts on counting these events. We use the 3-day totals in Fig. 8.4.7 to be sure to capture the extent of these extreme downpours. In any case, we can confirm that the period 1997 to 2014 experienced a cluster of heavier events as Howarth et al. have documented.

Howarth's most remarkable claim (317% increase in 6" days) is potentially misleading because it is a threshold statistic (see Section 8.4.2 above) and a ratio of small numbers over a short period. The result is not representative of *relative* extreme events for the whole region since the majority of stations never experienced a 6" total. Fig. 8.16 above determines the same number of events for each station (27 heaviest events) whose heaviest values ranged from 4.4" to 12.5" and their 27th heaviest values ranged from 3.3" to 5.0". This analysis thus allows each station to be equally represented. In

other words, if there is a region-wide increase in heavy events, it should be seen in the sum of all stations. Note too that the period of record here is 135 years vs. 36 years of Howarth et al. Except for three 5-year periods between 1995 and 2014 there is nothing statistically remarkable about the results in Fig. 8.4.7.

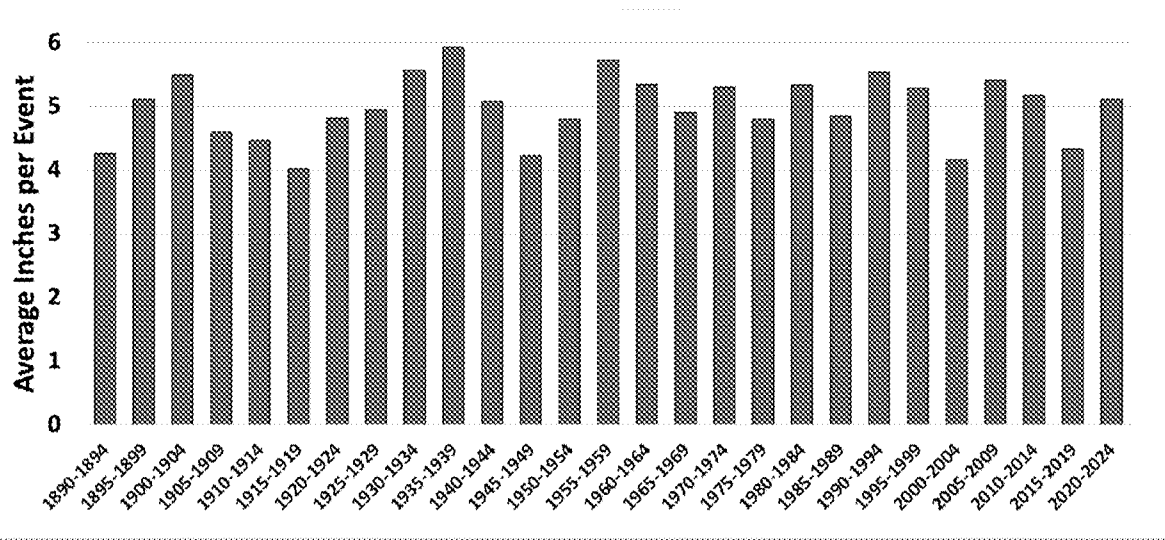


Figure 8.4.8. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

An interesting aspect of Northeast precipitation is that there has been no change in the amount of precipitation per heaviest event, as shown in Fig. 8.4.8. The trend is only $+0.02''/\text{decade}$. The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 8.4.6 and 8.4.7 suggest that though there was an uptick in the number of events during the period 1995 to 2014; the events, individually, are not becoming more intense.

Jong et al. (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, "The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s." The question then becomes, was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 8.17 where the amount-per-event has remained steady over the 135-year period.

For substantial urban areas there is some evidence to indicate the heaviest rainfall events may be redistributed due to the impact urban infrastructure has on the local weather (e.g., Pielke Sr. et al. 2011, Zhang et al. 2018, Yang et al. 2024). Yang et al. state, "Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with

dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 8.17.

In summary, the evidence from the historical record of extreme precipitation events in the CONUS is generally not consistent from region to region so that inferences regarding trends and their projections are wrought with significant uncertainty. In most regions and perhaps all, it is our opinion that the very nature of the erratic and episodic character of extreme precipitation events renders the discovery of statistically significant changes, including a relationship to CO₂ concentrations, a result yet to be achieved (McKittrick and Christy 2019).

8.5 Summary

Based on the content provided in the document, here are the five most important takeaways:

1. Limited Detection of Anthropogenic Signals: The IPCC has asserted high confidence in detecting an anthropogenic signal in only 4 out of 34 weather impact categories, and medium confidence in 4 more. For the remaining 26 categories, no anthropogenic signal is claimed to be detected.
2. Slow Emergence of Trends: Even under the most extreme forcing scenario (RCP8.5), the IPCC expects very few anthropogenic trends to emerge within this century for most weather impacts.
3. Natural Variability Dominance: Natural variability continues to dominate patterns of extreme weather systems. Simple assertions of trend detection are often complicated by regional heterogeneity and trend reversals over time.
4. RCP8.5 Scenario Implausibility: The document notes that the RCP8.5 scenario is described as an implausible high-end storyline, not a "base case" or "business-as-usual" projection.
5. Conflicting Messages on Attribution: The document mentions that AR6 (IPCC Sixth Assessment Report) offers conflicting messages about the attribution of extreme weather to anthropogenic causes, highlighting the complexity and uncertainty in this area of climate science.

These takeaways emphasize the nuanced and complex nature of attributing extreme weather events to climate change, and the importance of considering natural variability and uncertainty in climate projections.

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9. Changes in Sea level

Arguably the most important climate impact driver that is unambiguously associated with increasing temperatures is global sea level rise. Global warming increases sea level rise through thermal expansion of the volume of sea water and melting of glaciers and ice sheets. Another factor that influences sea level variations is land water storage. Regional sea level change is influenced by large-scale ocean circulation patterns, and geologic processes and deformation from the redistribution of ice and water. Local sea level rise is further influenced by vertical land motion from geologic processes, ground water withdrawal, and fossil fuel extraction.

The IPCC AR6 estimates that global mean sea level increased by 7.9 (5.9–9.8) inches between 1901 and 2018. The rate of sea level rise has accelerated in recent decades. At the ocean basin scale, sea levels have risen fastest in the Western Pacific and slowest in the Eastern Pacific over the period 1993–2018. The rate of global sea level rise is estimated to be 0.12 inches/year (for reference: 0.12 in is the height of two stacked pennies).

The observing systems for global sea level rise have advanced significantly in the satellite era, particularly with the advent of satellite altimeters since 1993. Local tide gauges have provided useful data for the past century, and even longer for a few locations. Following the end of the Little Ice Age in the mid-nineteenth century, tide gauges show that the global mean sea level began rising during the period 1820–1860.

9.1. U.S. coastal sea level rise

Observed and predicted rates of mean global sea level rise may have little relevance for specific locations. In Canada and Alaska (and also northern Washington), sea level is actually decreasing, owing to uplift from glacial rebound. Most of the Pacific coast has rates of sea level rise of 0 to 0.12 inches/year. The largest rates of sea level rise are on the Gulf coast (Louisiana and Texas) and in the mid-Atlantic states (Chesapeake Bay region).

Measurements of relative sea level rise from tide gauges conflate the rise in the volume of seawater with local vertical land motion. Hence in examining local sea level changes, it is important to also consider the local vertical land motion. Absolute local sea level rise is the sum of relative sea level rise and the local vertical land motion.

A wide range of processes can cause vertical land motion along the coasts, having amplitudes comparable to the sea level signals expected from land-ice melting or ocean thermal expansion. Vertical land motion on the coasts can locally exacerbate (subsidence/sinking) or mitigate (uplift) the risk of sea level rise. Local changes in sea level vary considerably from place to place and can deviate substantially from the rate of global mean sea level change. Human activities triggering subsidence are soil drainage (e.g. for urban development purposes) or subsurface mining of resources such as groundwater, oil or gas. The magnitude of relative sea level rise caused by human activities is often considerable. Local vertical land motion of relevance to local sea level change is best measured using a Global Positioning System (GPS) station located in the location as the tide gauge.

Table 8.1 shows absolute sea-level rise (ASLR) for selected locations, determined from the sum of uncorrected sea-level rise as estimated from tide gauge time series (RSLR) and the vertical land motion (VLM) measurements. The absolute sea level rise for each of these locations is significantly smaller than the measured relative sea level rise owing to local sinking of the land. More than half of the measured relative sea level rise is attributed to land sinking for these locations: San Francisco, Galveston, Grand Isle. For reference, the global average rate of absolute sea level rise is estimated to be 0.12 inches/year.

Table 8.1 Absolute sea level rise (inches/year) (RSLR plus VLM)

Location	RSLR	VLM	ASLR
San Francisco, CA	+0.08	-0.06	+0.02
Galveston, TX	+0.26	-0.19	+0.07
Grand Isle, LA	+0.36	-0.28	+0.08
St Petersburg, FL	+0.12	-0.02	+0.10
New York City, NY	+0.11	-0.05	+0.06

San Francisco Bay

Over the past 100 years, relative sea level in the San Francisco Bay area has risen by 7.8 inches, at an average rate of 0.08 inches/year (Figure 8.1). As shown in Table 6.1, San Francisco's vertical land motion is -0.06 inches/year (sinking), producing a recent rate of absolute sea level rise of +0.02 inches/year. Portions of Treasure Island, San Francisco International Airport, and Foster City are sinking as fast as 0.4 inches/year. Landfill zones are sinking due to soil compaction, at a rate as much as one-half inch per year, threatening coastal infrastructure including the San Francisco International Airport. The problems in the San Francisco Bay area have been caused primarily by sinking in landfill regions that were formerly wetlands, not by the slow creep of global sea level rise.

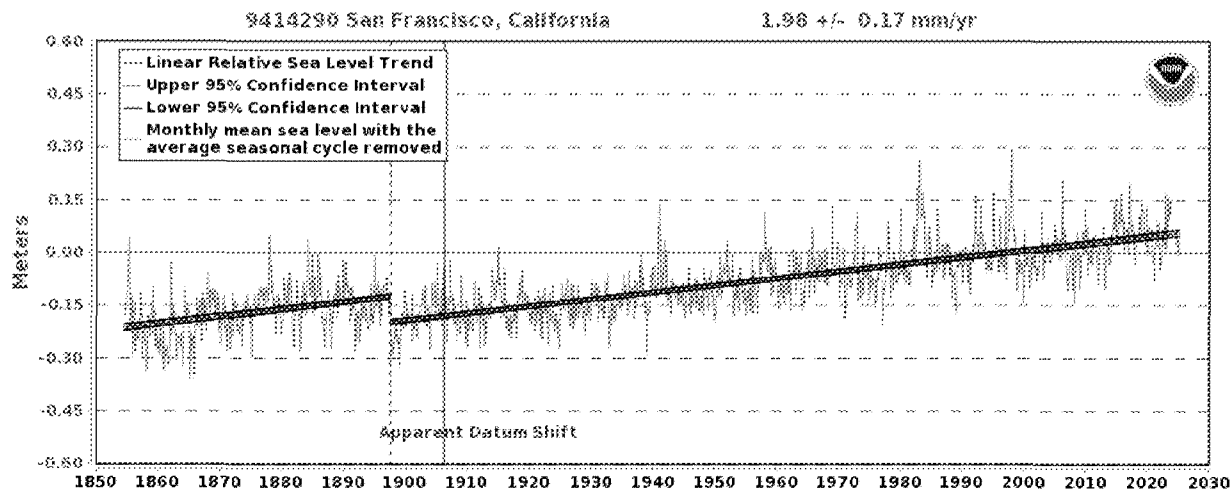


Figure 8.1. Tide gauge measurements at San Francisco, California, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=9414290 (downloaded 4/22/25).

Galveston - Houston

Long-term tide measurements at Galveston Pier 21 show sea level rise of 2.18 feet in the past century, or a rate of 0.26 inches/year (Figure 8.2). Vertical land motion (subsidence) at Galveston is estimated at -0.19 inches/year, yielding a value of absolute sea level rise of +0.07 inches/year (Table 8.1). The U.S. Geologic Survey found that most of the land-surface subsidence in the Houston-Galveston region has occurred as a direct result of groundwater withdrawals.⁶ This caused compaction of the aquifer sediments, mostly in the fine-grained silt and clay layers. By 1979, as much as 10 feet of subsidence had occurred in Houston.

Hurricanes are traditionally the major concern in the region. The 1900 hurricane that struck Galveston and killed between 6,000 and 12,000 people is still considered the United States' deadliest natural disaster.⁷ Hurricane Ike (2008) decimated large portions of the Bolivar Peninsula literally removing significant portions of the land mass.⁸ While only 17 people were killed in Texas, property damage exceeded \$50 billion.⁹ In 2017, Hurricane Harvey struck the region, bringing catastrophic rainfall-triggered flooding that inflicted over \$125 billion in damages.¹⁰

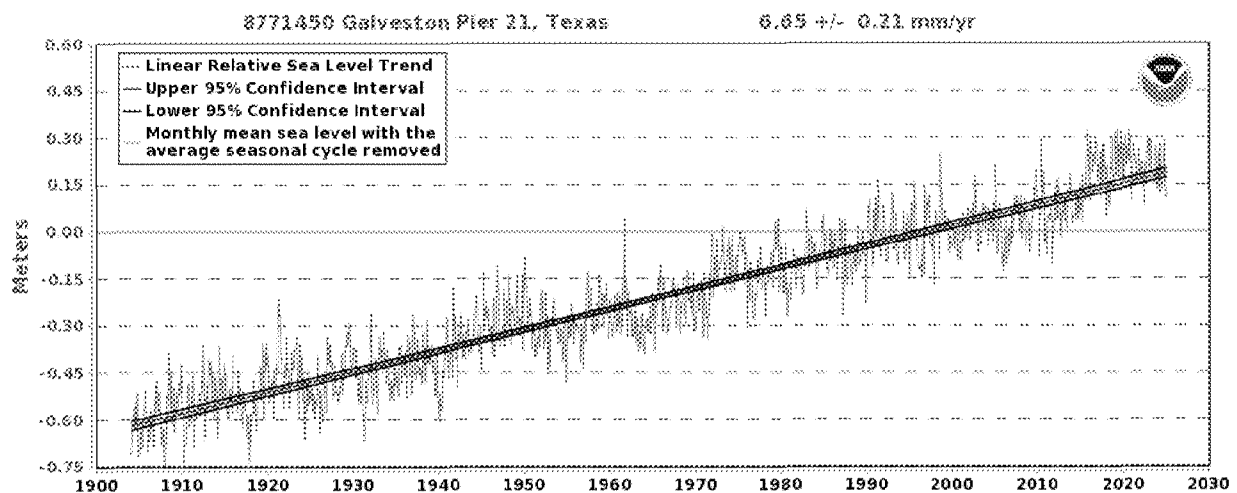


Figure 8.2. Tide gauge measurements Galveston Pier, TX, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8771450 (downloaded 4/22/2025).

New Orleans and the Mississippi delta

⁶ Kasmarek, M.C., and Ramage, J.K., 2017, Water-level altitudes 2017 and water-level changes in the Chicot, Evangeline, and Jasper aquifers and compaction 1973–2016 in the Chicot and Evangeline aquifers, Houston-Galveston region, Texas: U.S. Geological Survey Scientific Investigations Report 2017–5080, 32 p., <https://doi.org/10.3133/sir20175080>.

⁷ Weems, John Edward, "Galveston Hurricane of 1900", Texas State Historical Association, (March 15, 2016) <https://www.tshaonline.org/handbook/entries/galveston-hurricane-of-1900>.

⁸ "Galveston County, Texas, Faces Sea Level Rise and Storms", Union of Concerned Scientists, (June 23, 2017) <https://www.ucs.org/resources/galveston-county-texas-faces-sea-level-rise-and-storms>.

⁹ White, Audrey, "Galveston Still Healing 5 Years After Hurricane Ike", The Texas Tribune, (April 26, 2013) <https://www.texastribune.org/2013/04/26/galveston-still-healing-5-years-after-hurricane-ike/>.

¹⁰ NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2025). <https://www.ncei.noaa.gov/access/billions/>, DOI: 10.25921/stkw-7w73

There are long-term tide gauge measurements at Grand Isle, Louisiana, respectively estimating that sea level has risen slightly more than 3 feet over the last 100 years and at an average rate of 0.36 inches/year (Figure 8.3). Vertical land motion (subsidence) is estimated -0.28 inches/year at Grand Isle. From Table 6.1, the absolute sea level rise is +0.08 inches/year at Grand Isle.

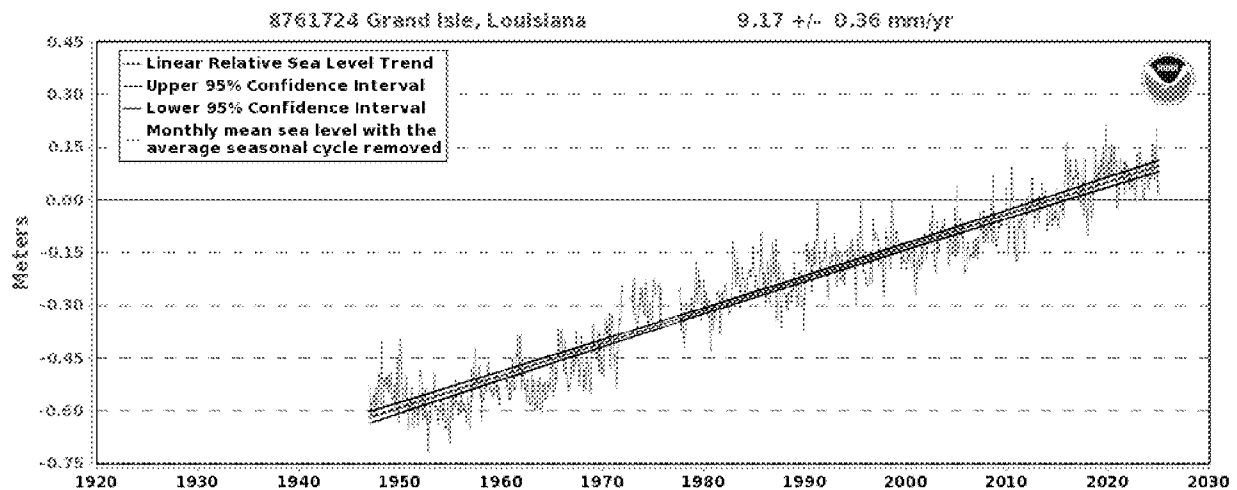


Figure 8.3. Tide gauge measurements at Grand Isle, LA, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8761724 (downloaded 4/22/25).

The issues of sea level rise and land loss in the Mississippi delta region are complex, with geological subsidence and the decline in sediment transported by the Mississippi river being the dominant drivers. Due to the construction of dams in the basin since the 1950s, the suspended sediment load of the Mississippi River has decreased by ~50%.¹¹ A new subsidence map of coastal Louisiana finds the coastal region to be sinking at about one third of an inch per year.¹² For a city whose elevation averages one to two feet below sea level, sea level rise from human caused warming is not the dominant driver for the problems that New Orleans is facing.

New York City

New York City is particularly vulnerable to the effects of sea level rise because it is built primarily on islands and has 520 miles of coastline. In New York City, relative sea level has risen over 11 inches over the past century, at an average rate of 0.11 inches/year (Figure 8.4). Vertical land motion in the New York City area is occurring at a rate of -0.05 inches/year (subsidence), corresponding to roughly 5 inches per century. From Table 6.1, the absolute rate of sea level rise at The Battery location is 0.06 inches/year, or about 55% of the measured relative sea level rise.

¹¹ Jillian M. Maloney et al., "Mississippi River Subaqueous Delta Is Entering a Stage of Retrogradation," *Marine Geology* 400 (June 2018): 12–23, <https://doi.org/10.1016/j.margeo.2018.03.001>.

¹² Jaap H. Nienhuis et al., "A New Subsidence Map for Coastal Louisiana," *GSA Today* 27, no. 6 (June 2017): 28–29, <https://doi.org/10.1130/GSATG337GW.1>.

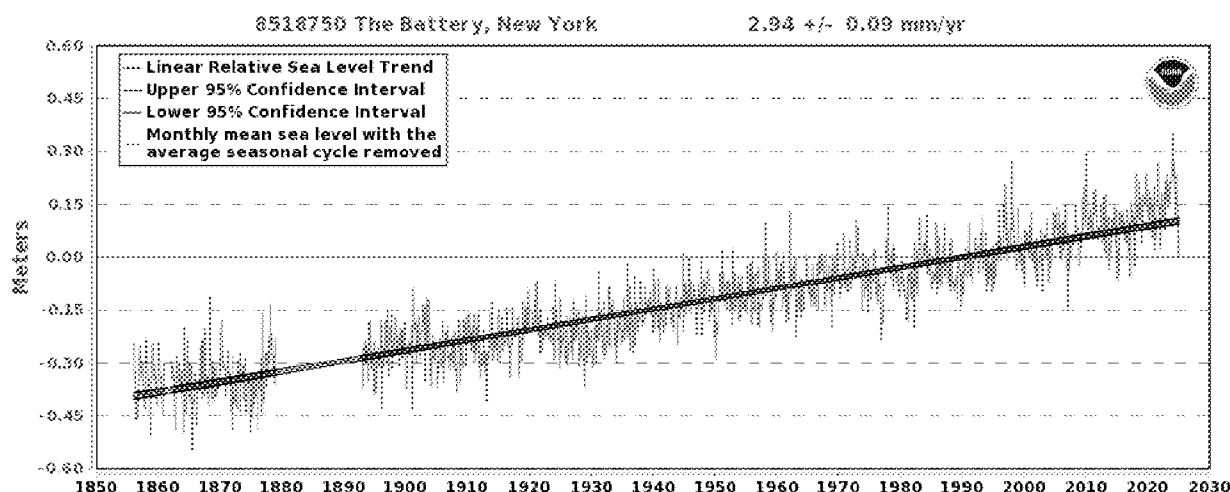


Figure 8.4. Tide gauge measurements at The Battery, New York, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750 (downloaded 4/22/25).

Following Hurricane Sandy, New York has developed a comprehensive plan: *City of New York: Building a Stronger, More Resilient New York*.¹³ A broad range of coastal protection measures are outlined that match the risks facing a given area: increase coastal edge elevations, minimize upland wave zones, infrastructure to protect against storm surge, improve coastal design and governance, restore estuaries wetlands, coastal nourishment, site elevation, and drainage systems.

9.2. Sea level rise projections

The concern over sea level rise is not about the 8 inches or so that global mean sea level has risen since 1900. Rather, the concern is about projections of 21st century sea level rise based on climate model-based projections of human-caused global warming.

The IPCC AR6 finds that there is high agreement across published global mean sea level projections for 2050 and there is little sensitivity to emissions scenarios. Considering only projections incorporating ice-sheet processes in whose quantification there is at least medium confidence, the global sea level projections for 2050, across all emissions scenarios, fall between 3.94 and 15.75 inches (5th–95th percentile very likely range) relative to the 1995–2014 baseline period.

Conversely, there is low agreement across published global mean sea level projections for 2100, particularly for higher emissions scenarios. Considering only projections representing processes in whose quantification there is at least medium confidence, the AR6 global mean sea level projections for 2100 lie between 7.87 and 39.37 inches (5th–95th percentile very likely range) under the medium emissions scenario SSP2–4.5. There is deep uncertainty surrounding projections of sea level rise to 2100, particularly for the higher emissions scenarios.

¹³ City of New York, *A Stronger, More Resilient New York* (New York: City of New York, June 2013), http://s-media.nyc.gov/agencies/sirr/SIRR_singles_Hi_res.pdf.

In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995-2014), almost half of the sea level rise has already occurred by 2025. From the tide gauge measurements in Figures 8.1-8.4, there is no obvious acceleration in sea level rise beyond the historical average rate of sea level rise.

9.3. Summary

Since 1900, global sea level has risen by about 8". Sea level change along U.S. coasts is highly variable, associated with local variations in processes that contribute to sinking and also ocean circulation patterns. The highest levels of sea level rise along U.S. coasts are Galveston, New Orleans, and the Chesapeake Bay regions — each of these locations is associated with substantial local sinking that is unrelated to climate change.

Extreme projections of global sea level rise are associated with the implausible extreme emissions scenario and inclusion of poorly understood processes associated with hypothesized ice sheet instabilities. In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995-2014), almost half of the sea level rise has already occurred by 2025 and at a lower rate than predicted. From the tide gauge measurements in Figures 8.1-8.4, there is no obvious acceleration in sea level rise beyond the historical average rate of sea level rise.

Part III: Impacts on Ecosystems and Society

10. Climate change and US agriculture

10.1. Econometric analyses

Econometric analyses of the effects of climate change on agriculture have sought to integrate information about long term crop yield changes in response to temperature and precipitation changes under assumptions about adaptive behavior by farmers. One method focuses on variations in agricultural land values. The rationale is that if climate change is a long-term net benefit for agriculture it should translate into higher market values for agricultural land, and vice versa. While individual crops might benefit from or be harmed by climate change, once the adaptive responses of farmers are taken into account the value of farmland represents an index of whether the changes are expected to be beneficial or not. Mendelsohn et al. (1994) examined the relationship between historical climatic variations on agricultural land values and concluded global warming would be slightly beneficial to American agriculture.

The Mendelsohn et al. method, called Ricardian analysis after David Ricardo, the 19th century British economist who pioneered the study of land values, attracted subsequent criticism from authors who argued it failed to account for differences in land values attributable to fixed locational characteristics like soil quality, and non-climatic changes including nearby urbanization. Deschênes and Greenstone (2007) looked at agricultural profits instead of land values and reached similar conclusions to Mendelsohn et al. (1994), namely that past climatic variations had relatively little effect on farm profitability and that warming would likely yield small overall benefits for the US agricultural sector. However a subsequent exchange with critics led them (Deschênes and Greenstone 2012) to revise their conclusions and project potentially large losses in US agriculture due to climate warming. Burke and Emerick (2016) looked at temperature variations over 1980 to 2000 and argued that farmers were not as able to adapt to temperature changes as the Ricardian method assumes and that climate change would have large negative impacts on corn and soy yields. Schlenker and Roberts (2009) similarly argued that yield gains to past warming would not carry over to the future and corn and soy yields would sharply decrease this century due to climate change.

Two recent studies have argued that pessimistic findings such as these are not robust. Ortiz-Bobea (2019) argued that land values aggregate farm and non-farm influences and the latter need to be filtered out. He developed a data set using cash rents for agricultural activity as a measure of land value specifically for farming activity. Whereas the land value model implied future losses under climate warming, the same model estimated using cash rents did not, leading the author to conclude the pessimistic results were due to using an inaccurate measure of the returns to farming activity. Bareille and Chakir (2023) assembled a large data base on farm sale prices in France for properties that sold twice between 1996 and 2019. They could replicate pessimistic results showing negative effects of warming on agricultural land values using conventional econometric modeling. But by taking advantage of the repeat sales data, which provides information on site-specific changes in land prices, they found the results reversed and implied that climate change will be very beneficial for French agriculture. The authors concluded that, taking adaptation into account, a warming climate would yield positive benefits for French agriculture that were between two and 20 times larger than had previously been estimated.

On average, with full adaptation, they concluded that climate changes under the medium RCP4.5 scenario could double the value of French farmland by 2100.

A major deficiency of all these studies, however, is that they omit the role of CO₂ fertilization. Climate change as it relates to this report is caused by GHG emissions, chiefly CO₂. The econometric analyses referenced above focus only on temperature and precipitation changes and do not take account of the beneficial growth effect of the additional CO₂ that drives them. As explained in Chapter 2 CO₂ is a major driver of plant growth so this omission biases the analysis towards underestimation of the benefits of climate change on agriculture.

10.2. Field studies of CO₂ enrichment

One of the ways the effect of CO₂ on crop growth has been studied is through “free air enrichment experiment” or FACE plots, in which small chimneys are placed in fields surrounding plants and the growth response to elevated CO₂ under varying weather conditions are recorded. Ainsworth et al. (2020) summarizes results from about 250 such studies. They found that elevation of CO₂ by 200 ppm cause an average 18% increase in crop yield in C3 plants. C4 plants exhibited benefits mainly under drought conditions.

In addition to FACE plot experiments there have been thousands of laboratory experiments on the effects of CO₂ on all kinds of plant growth. Here we review some of the results on key US agricultural crops.

Soybean

Studies on the impact of elevated CO₂ on Soybean (*Glycine max* (L.) Merr.) plants in the water-deficient region of Huang-Huai-Hai Plain, China, showed that elevated CO₂ concentrations resulted in improved photosynthesis rate, water use efficiency and growth (Li, 2013) under both normal conditions and drought conditions. The CO2Science.org website reports on 108 published experiments between 1985 and 2019 exposing soybean to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +50.9 percent. In addition there were 10 studies reporting on +600 ppm CO₂ enrichment, resulting in an average increase in photosynthesis of 90.3%.

Maize (corn)

The CO2Science.org website reports on 28 published experiments between 1983 and 2018 exposing corn (*Zea mays* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +23.7 percent. Corn also benefits from increased drought tolerance under elevated CO₂. An experimental study (Allen Jr, 2011) exposed plants to water stress conditions in sunlit controlled-environment chambers at 360 ppm (ambient) and 720 ppm (elevated) CO₂. The drought stress caused a 41% loss of growth under ambient CO₂ but only a 13% loss under elevated CO₂.

Wheat

The CO2Science.org website reports on 92 published experiments between 1983 and 2020 exposing common wheat (*Triticum aestivum* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +67.6 percent. Blandino (2020) measured the yield as well as nutritional quality of an “improver” hybrid wheat variety and its parents under elevated CO₂ levels (+166 ppm). They reported a grain yield increase of +16% but a 7% decrease in grain protein levels. But they found that the food quality of different wheat varieties responded differently to elevated CO₂ levels, so that with proper varietal selection end-users can select wheat types that best take advantage of the elevated CO₂.

Further evidence

A 2021 report from the US National Bureau of Economic Research (Taylor and Schlenker 2021) used satellite-measured observations of outdoor CO₂ levels across the United States, matched to county-level agricultural output data and other economic variables. After controlling for the effects of weather, pollution and technology the authors concluded that CO₂ emissions had boosted US crop production since 1940 by 50 to 80 percent, attributing much larger gains than had previously been estimated using FACE experiments. They found that every ppm of increase in CO₂ concentration boosts corn yields by 0.5 percent, soybeans by 0.6 percent, and wheat by 0.8 percent.

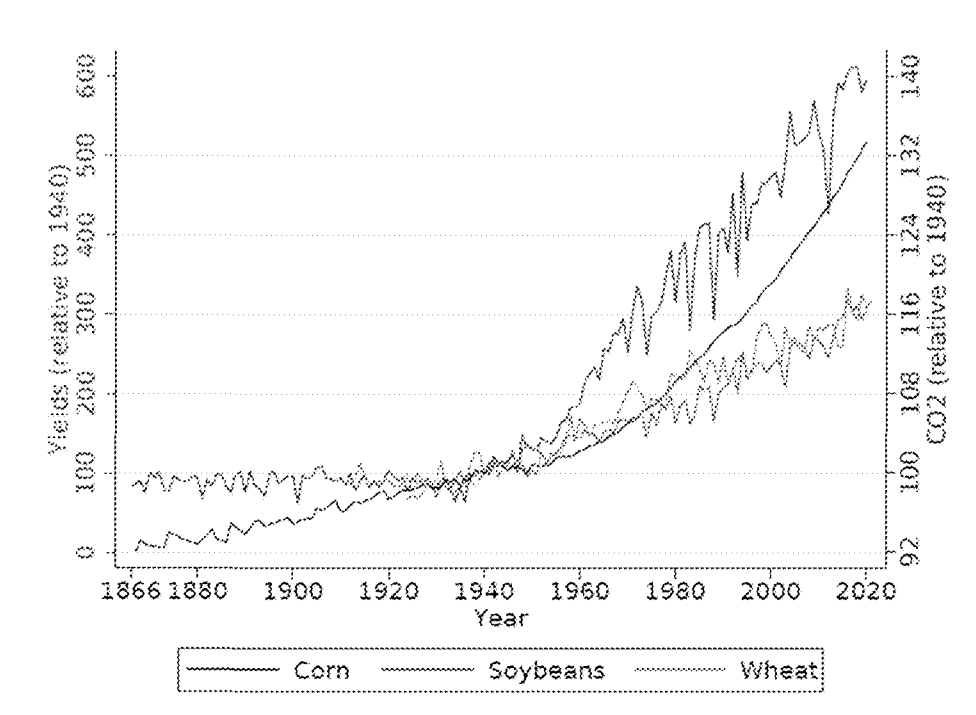


Figure 10.1: US average CO₂ levels and yields of corn, soy and wheat all normalized so 1940=100. Source: Taylor and Schlenker (2021)

Beyond growth benefits, extra CO₂ boosts plant resilience to heat. Deryng et al. (2016) surveyed all available evidence regarding how wheat, maize, rice and soybean will grow under a combination of climate warming and rising CO₂ levels. They concluded that warming would, eventually, have a negative effect on plant growth but it would be fully compensated by the extra CO₂ for wheat and soybean, and almost fully for rice and maize. And as discussed in Chapter 2, plants use water more efficiently when there is more CO₂ in the air.

Deryng et al. (2016) surveyed evidence on crop water productivity (CWP), i.e. yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them and once it was taken into account all regions showed a net CWP gain. Deryng et al (2016) also reported that negative impacts on wheat and soybean yields were fully offset by CWP gains, and mitigated by up to 90% for rice and 60% for maize.

Similar to this, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

10.3. Crop modeling meta-analyses

Notwithstanding the abundant evidence for the direct benefits of CO₂ and of CO₂-induced warming on crop growth, in 2023 the US Environmental Protection Agency (EPA 2023) boosted its estimate of the Social Cost of Carbon (SCC) about five-fold based in large part on a very pessimistic 2017 estimate of global agricultural damages from climate warming (Moore et al., 2017). One of the two damage models used by the EPA attributed nearly half of the 2030 SCC to projected global agricultural damages based on the Moore et al. (2017) analysis. This study was a meta-analysis of crop model studies simulating yield changes for agricultural crops under various climate warming scenarios. Moore et al. projected declining global crop yields for all crop types in all regions due to warming.

McKittrick (2025) re-examined the Moore et al. database and found that, while it claimed to cover 1,722 studies, only half the entries ($N=862$) had complete records, so that the sample available for regression analysis was much smaller than both studies indicated. McKittrick noted that the variable most commonly missing was the change in ambient CO_2 and found that in many cases these could be recovered from the underlying studies or the original climate scenario tables. He thereby increased the usable sample size by 40 percent. The crop yield projections incorporating the newly available data changed considerably. As shown in Figure 10.2, whereas the partial data set implied warming would decrease yield (blue lines), the complete data set implied constant or increase global yields, even out to 5°C warming (green lines).

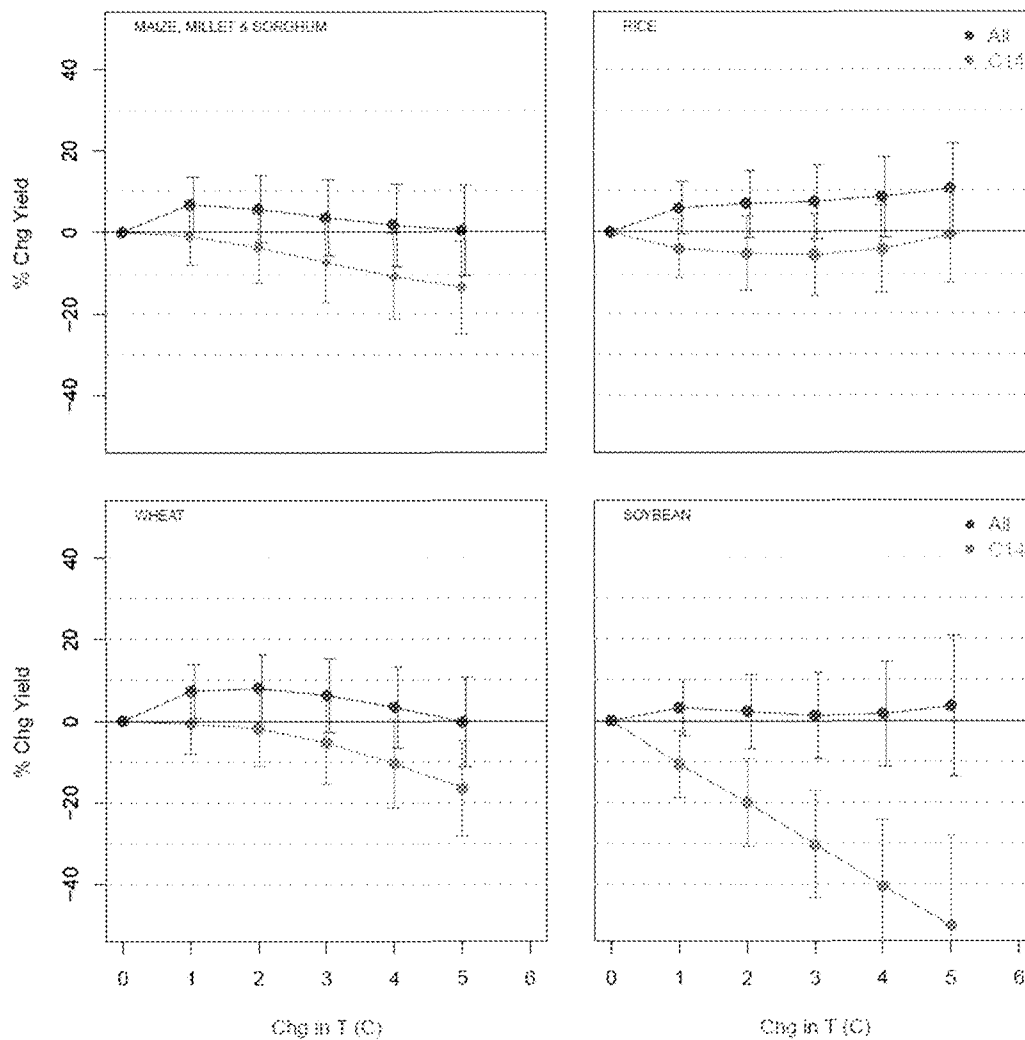


Figure 10.2 Crop yields under CO_2 -induced climate warming. Blue: as published in Moore et al. (2017). Green: after including omitted data. Source: McKittrick (2025).

In summary, there is abundant evidence going back decades that rising CO₂ levels benefit plants including agricultural crops, and that CO₂-induced warming will be a net benefit to US agriculture. The warming since 1981, in combination with adaptive behaviour by farmers, has been beneficial on its own for maize. The increased ambient CO₂ has also boosted productivity of all major US crop types. Various attempts to argue that CO₂-induced warming will harm agriculture do not hold up under scrutiny.

Deschênes, Olivier and Michael Greenstone (2007) The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather *American Economic Review*. Feb 2007, Vol. 97, No. 1: Pages 354-385

Deschênes, Olivier and Michael Greenstone (2012) The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Reply to Comment *American Economic Review*. 102, no. 7: 3761-3773. <http://hdl.handle.net/1721.1/82641>

Ortiz-Bobea, Ariel (2019) The role of nonfarm influences in ricardian estimates of climate change impacts on US agriculture. *American Journal of Agricultural Economics*. 102 (3), 934–959.

Schlenker, Wolfram and Michael Roberts (2009) Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences* 106 (37) 15594-15598 <https://doi.org/10.1073/pnas.0906865106>

11. Managing risks of extreme weather

11.1. Socioeconomic context

Risks from human-caused climate change are convoluted with natural weather and climate variability, and are dominated by the exposure of wealth in coastal and other disaster-prone regions and vulnerabilities of poorer populations. The evolution of climate risk in the U.S. has been dominated by societal factors, rather than by changes to the actual weather and climate hazards. Deaths from weather disasters have decreased substantially since 1900, even as US population grew from 76 million in 1900 to over 331 million in 2020. For example, the Galveston hurricane killed over 8,000 people in 1900 (0.01% of the US population), whereas the worst recent disaster, Hurricane Katrina in 2005, killed 1800 people (or 0.0006% of the US population).

Technological advances have substantially reduced losses from extreme weather events. Early warning systems, satellite monitoring, and improved weather forecasting have reduced deaths, although exact numbers are hard to quantify. <https://www.nber.org/papers/w31361>

US weather forecasting has been estimated to reduce losses from weather events with an annualized benefit of \$31.5B, protecting lives, property, and supporting agriculture and transportation <https://nap.nationalacademies.org/read/12888/chapter/2> Improved hurricane forecasts have reduced pre- and post-landfall spending, with annual per hurricane cost reductions estimated at \$5B

<https://www.nber.org/digest/202409/value-improving-hurricane-forecasts>

Infrastructure improvements have contributed to substantial reductions in losses from extreme weather events. Building codes, such as those implemented in Florida after Hurricane Andrew (1992) have reduced losses by ensuring structures can withstand high winds and floods. Homes built after 2002 showed minimal damage during Hurricane Michael (2018), unlike older homes.

<https://www.fema.gov/case-study/role-floridas-building-codes-2018-hurricane-michael>. Sea walls, like the Galveston Seawall, protect against wave action and storm surge. The New Orleans Hurricane and Storm Damage Risk Reduction System successfully mitigated storm surge during Hurricane Isaac (2012). Inland dams in the US help control flooding by storing excess water during heavy rains. It is estimated that the Tennessee Valley Authority (TVA) dams prevent about \$309M in annual flood damage in the TVA region and along the Ohio and Mississippi Rivers <https://www.tva.com/environment/managing-the-river/flood-management>

During Hurricane Helene (2024), TVA's strategies prevented approximately \$406M in potential damages. <https://www.publicpower.org/periodical/article/tva-flood-mitigation-strategies-prevented-approximately-406-million-potential-damages>

11.2. Data challenges

Since 1980, NOAA has provided a count of annual U.S. weather-related disasters that it estimates to have exceeded \$1Billion (inflation adjusted), showing a substantial increase starting in 2008. NOAA and other government officials have cited the upward trend in the BDD series as evidence that climate change is making extreme weather worse (Pielke Jr. 2024). But over time, population and wealth have increased dramatically in the US, so when an extreme weather or climate event occurs, there is more damage even if there is no underlying trend in the frequency or intensity of extreme weather. A recent estimate finds that losses per weather disaster are down by about 80% since 1980, as a proportion of GDP.

<https://drive.google.com/file/d/1MvgwcWaimcn1oHODqNZDG1fXF4M5Idnn/view>

Pielke Jr. (2024) argued that in addition to relying on opaque data sources and unreported adjustments NOAA failed to normalize its Billion Dollar Disaster (BDD) data series properly for changes in population exposure and wealth. In May 2025 NOAA announced it has withdrawn the billion dollar disaster product from publication (Pielke Jr. 2025).

In summary, trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. And finally, the US economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages.

Pielke Jr., Roger (2024) Scientific integrity and U.S. "Billion Dollar Disasters" *NPJ Natural Hazards* 1
<https://www.nature.com/articles/s44304-024-00011-0>

Pielke Jr., Roger (2025) "RIP NOAA's Billion Dollar Disasters" Substack essay May 8, 2025
<https://rogerpielkejr.substack.com/p/rip-noaas-billion-dollar-disasters>

12. Mortality from temperature extremes

12.1. Heat and cold risks

Changes in temperature extremes are among the most certain impacts expected in a warming globe -- extreme heat events are expected to become more frequent while extreme cold events become less frequent. This pattern is evident in the historical period (as discussed in Section XX) and is expected to intensify with continued warming.

Mortality during heat extremes is typically caused by heat stroke and heat exhaustion, while mortality during cold extremes is typically caused by hypothermia and heart strain. It is well known that global mortality is substantially greater for extreme cold than for extreme heat.^{14,15}

Specific to the U.S., extreme heat and extreme cold both kill hundreds of people each year.; however, different approaches to assessing heat/cold mortality produces different results. The Center for Disease Control (CDC) National Center for Health Statistics Compressed Mortality Database, which is based on death certificates, indicates that about twice as many people die of “excessive cold” conditions in a given year than of “excessive heat.”^{16,17}

A 2015 epidemiological study of deaths in published in *The Lancet* found that cold-related deaths in the U.S. were about a factor of fifteen higher than heat-related deaths.¹⁸ However, the study did not adjust for the seasonal cycle in mortality rates, which tend to increase during the winter months due to non-weather factors like influenza.¹⁹ A more recent paper found that 86% of temperature-related deaths in the U.S. are due to cold-related mortality.²⁰

¹⁴ Qi Zhao et al., “Global, Regional, and National Burden of Mortality Associated with Non-Optimal Ambient Temperatures from 2000 to 2019: A Three-Stage Modelling Study,” *The Lancet Planetary Health* 5, no. 7 (July 2021), [https://doi.org/10.1016/s2542-5196\(21\)00081-4](https://doi.org/10.1016/s2542-5196(21)00081-4).

¹⁵ <https://ourworldindata.org/part-one-how-many-people-die-from-extreme-temperatures-and-how-could-this-change-in-the-future>

¹⁶ Brett R. Scheffers et al., “The Broad Footprint of Climate Change from Genes to Biomes to People,” *Science* 354, no. 6313 (November 11, 2016): aaf7671, <https://doi.org/10.1126/science.aaf7671>.

¹⁷ Rachel H. Alinsky, Scott E. Hadland, J. Deanna Wilson, Pamela A. Matson, and Brendan Saloner, “Trends in Polysubstance Overdose Deaths Involving Opioids, Stimulants, and Benzodiazepines by Race and Ethnicity in the US, 2007-2021,” *JAMA Network Open* 7, no. 3 (March 2024): e238249, <https://doi.org/10.1001/jamanetworkopen.2024.8249>.

¹⁸ Lancet Commission on Climate and Health, “Health and Climate Change: Policy Responses to Protect Public Health,” *The Lancet* 386, no. 10006 (November 7, 2015): 1861–1914, [https://doi.org/10.1016/S0140-6736\(15\)60854-6](https://doi.org/10.1016/S0140-6736(15)60854-6).

¹⁹ Bob Henson, “Which Kills More People: Extreme Heat or Extreme Cold?” *Weather Underground*, January 22, 2019, <https://www.wunderground.com/cat6/Which-Kills-More-People-Extreme-Heat-or-Extreme-Cold>.

²⁰ Tarik Benmarhnia et al., “Deaths Attributable to Heat and Cold: Comparison of Data Sources and Evaluation of Inconsistencies,” *GeoHealth* 8, no. 3 (March 2024): e2023GH000799, <https://doi.org/10.1029/2023GH000799>.

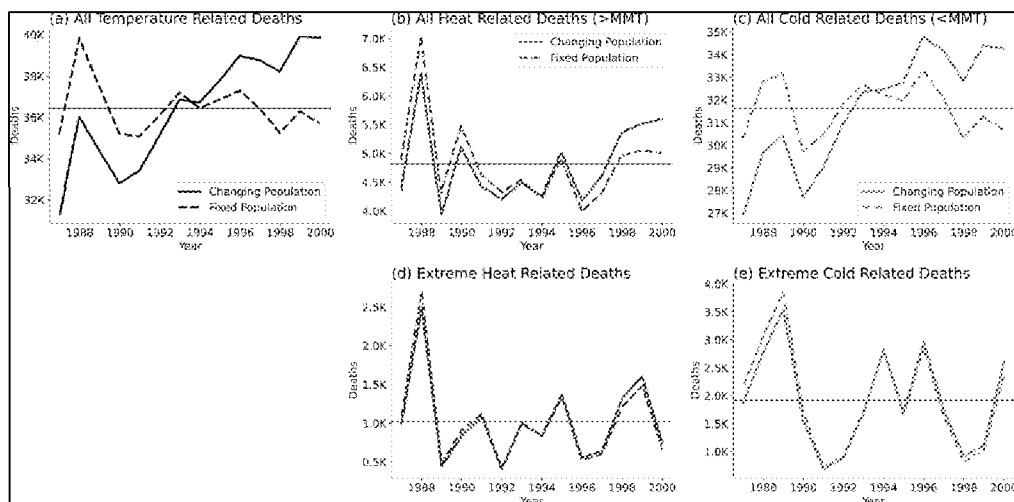


Figure 12.1: Time series of temperature-related deaths across all 106 cities. (a) The solid line represents total temperature-related deaths, while the dashed line indicates temperature-related deaths with a fixed population (average population from the 1987–2000 period). (b) Similar to (a), but for heat-related deaths. (c) Similar to (a), but for cold-related deaths. (d) Time series of deaths occurring in temperatures above the 97.5th percentile. (e) Similar to (d), but for temperatures below the 2.5th percentile. From <https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2023GH000799>

The IPCC AR6 Working Group 2 Chapter 16.2.3.5 states how heat-related mortality is declining over time:²¹

“Heat-attributable mortality fractions have declined over time in most countries owing to general improvements in health care systems, increasing prevalence of residential air conditioning, and behavioral changes. These factors, which determine the susceptibility of the population to heat, have predominated over the influence of temperature change.”

A 2011 study of 40 major US cities between 1975 and 2004, found that heat wave mortality had decreased, in spite of rising temperatures, due to adaptation.²² Likewise Davis et al. (2003) examined heat-related mortality in 28 U.S. cities from the 1960s to the end of the 1990s and found that heat-related mortality declined by three-quarters over the sample period. Bobb et al. (2014) examined mortality data for 106 million people in over 100 cities U.S. cities and found a 60% decline in average heat-related mortality over the period 1987–2005, from 51 per thousand deaths to 19. They furthermore found that the greatest drop was among seniors over the age of 75. In a study of 42 million

²¹ B. O'Neill et al., “Key Risks Across Sectors and Regions,” in *Climate Change 2022: Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, CH: Intergovernmental Panel on Climate Change, 2021), 2411–2538.

²² Keith T. Ingram, Carolyn W. Furman, and John W. Jones, “Climate Change Impact and Adaptation Assessment: A Guide for Coastal Resources Managers,” *Weather, Climate, and Society* 3, no. 4 (October 2011): 234–249, <https://doi.org/10.1175/WCAS-D-11-00055.1>.

deaths in 211 U.S. cities from 1962 to 2006. Nordio et al. (2015) found a more than 90 percent decline in the risk of mortality from excess heat.

In the context of large declines in heat-related mortality, by reducing mortality from cold events rising temperatures are associated with a net saving of lives.

It is both disappointing and telling to see how the IPCC misrepresents the situation in its AR6 Synthesis report. Section A.2.5 of that document states: “In all regions increases in extreme heat events have resulted in human mortality and morbidity (*very high confidence*).” But it is silent on the larger decline of deaths during extreme cold events.

12.2. The importance of adaptation

The observed decline in US heat-related mortality has been specifically attributed to adaptation. Wang et al. (2018) exploited the spatial variability of heatwave-related mortality across 209 U.S. cities from 1962 to 2006. While simple correlation appeared to imply an increase in mortality risk during heatwaves, accounting for adaptation to heatwave intensity caused the effect to fall to near zero and become statistically insignificant. They used the results of their epidemiological model to project heat-related mortality out to 2050 under four RCP warming scenarios (including RCP8.5) with and without adaptive behavior. Assuming people continue to adapt to the heatwave risks in the regions in which they live Wang et al. project not only no increase in heat-related mortality but an overall decrease for the US as a whole. They conclude that “Ignoring adaptation would result in a substantial overestimate of future mortality related to heat waves... Accounting for adaptation, the overall heat-related mortality by 2050 would not change substantially over time compared to 2006.”

12.3. Mortality risks and energy costs

A 2016 study of US long term mortality risks associated with temperature variations (Barreca et al. 2016) showed that increases in mortality across the US are associated both with cold weather and hot weather. But over time, the introduction of electricity and the adoption of central heating and air conditioning (AC) dramatically reduced both risks, especially those associated with hot weather. Prior to 1960, a day above 90°F (32°C) added 2.2 percent to the average mortality risk rate, but after 1960 the same weather added only 0.3 percent to mortality risk, an 85 percent reduction. Prior to 1960 temperatures below 39°F (4°C) added about 1 percent to mortality risk but after 1960 the same weather only added about half that amount. Adaptation through conventional household improvements dramatically reduced public vulnerability to weather extremes. The entire reduction in hot weather mortality was attributable to widespread adoption of indoor AC, which depended on the availability of reliable and affordable electricity.

The corollary of this finding is that the use of heating and cooling systems depends on energy being affordable. Doremus et al. (2022) showed that wealthy and poor households in the US adjust their energy expenditures at similar rates in response to moderate temperature swings, but not in response to extreme temperature swings. When temperatures swing to very cold levels (< 5°C) energy spending in high-income households rises by 1.2 percent but in low-income households by only 0.5 percent. On very

hot days (>30°C) electricity spending in high-income households rises by 0.5 percent but does not change at all in low-income households. The latter result is observed even in subsamples where all households have AC. The implication is that even with widespread adoption of home heating and cooling systems, inability to afford energy leaves low-income households exposed to weather extremes.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro, “Adapting to climate change: The remarkable decline in the US temperature mortality relationship over the twentieth century,” *Journal of Political Economy*, 2016, 124 (1), 105–159.

J.M. Doremus, I. Jacqz and S. Johnston (2022), “Sweating the energy bill: Extreme weather, poor households, and the energy spending gap.” *Journal of Environmental Economics and Management*, doi: <https://doi.org/10.1016/j.jeem.2022.102609> .

Nordio, Francesco, Antonella Zanobetti, Elena Colicino, Itai Kloog and Joel Schwartz (2015). “Changing patterns of the temperature–mortality association by time and location in the US, and implications for climate change” *Environment International*, Volume 81, pp 80-86
<https://doi.org/10.1016/j.envint.2015.04.009>.

Wang, Yan, Francesco Nordio , John Nairn , Antonella Zanobetti and Joel D. Schwartz (2018) “Accounting for adaptation and intensity in projecting heat wave-related mortality” *Environmental Research* 161 pp. 464—471. <https://doi.org/10.1016/j.envres.2017.11.049>

Bobb JF, Peng RD, Bell ML, Dominici F. (2014) Heat-related mortality and adaptation to heat in the United States. *Environmental Health Perspectives* 122:811–816;
<https://ehp.niehs.nih.gov/doi/full/10.1289/ehp.1307392>

Davis, Robert E., Paul C. Knappenberger, Patrick J. Michaels and Wendy M. Novicoff (2003) “Changing Heat-Related Mortality in the United States” *Environmental Health Perspectives* 111(14) November 2003 pp. 1712—1718.

13. Climate change, the economy and the Social Cost of Carbon

13.1. Climate change and economic growth

13.1.1 Overview: climate is a relatively minor issue for a modern economy

It has long been noted that economies tend to do poorly in very cold and very hot regions, with the optimum somewhere in between (Nordhaus 2006). Temperature-sensitive economic activity migrates, whenever possible, to where it is best suited, and society always adapts to the local climate. Based in part on these observations, in 1992 Thomas Schelling, then President of the American Economic Association, argued that any effects climate change on US economic activity would be small relative to the many other changes that would happen.

... Manufacturing rarely depends on climate, and where temperature and humidity used to make a difference, air conditioning has intervened. When Toyota chooses among Ohio, Alabama, and Southern California for locating an automobile assembly, geographical considerations are important, but not because of climate... Finance is little affected by climate; similarly for health care, or education, or broadcasting. Transportation can be affected, but improvements in all-weather landing and take-off in the last 30 years are greater than any differences that climate makes. If the average effect is a warming, iced waterways and snow removal may decline in importance. Construction is affected, mainly by cold, and if the average effect is in the direction of warming, construction may benefit slightly.

It is really agriculture that is affected. But even if agricultural productivity declined by a third over the next half century, the per capita GNP we might have achieved by 2050 we would achieve only in 2051. ...

I conclude that in the United States, and probably Japan, Western Europe, and other developed countries, the impact on economic output will be negligible and unlikely to be noticed.

(Schelling 1992, emphasis added)

Thirty years later virtually the identical point was made by the IPCC itself in the Fifth Assessment Report:

For most economic sectors, the impact of climate change will be small relative to the impacts of other drivers. Changes in population, age, income, technology, relative prices, lifestyle, regulation, governance, and many other aspects of socioeconomic development will have an impact on the supply and demand of economic goods and services that is large relative to the impact of climate change.

(Arent et al. 2014, emphasis added)

That statement is validated by experience. Since 1900, the average global surface temperature anomaly warmed 1.3°C, about as much as the IPCC predicts will occur in the next century under a moderate emissions scenario. But even as the globe warmed and the population quintupled, humanity prospered as never before. For example, global average lifespan went from thirty-two years to seventy-two years, economic activity per capita grew by a factor of seven, and the death rate from extreme weather events plummeted by a factor of fifty!

While extreme weather events are costly, in all modern economies they are becoming steadily less and less important (Formetta and Feyen 2019). Since 1990 weather-related disaster losses have declined as a proportion of global GDP (Pielke Jr 2018, 2020) as have mortality risks (Formetta and Feyen 2019). While economic weather-related insurance payouts are rising, this is fully explained by the growth in the size of the economy and the value of the insured asset stock. Past increases in episodes extreme weather have not had a significant effect (positive or negative) on the market value of insurance firms (Hu and McKittrick 2015). Nor have past extreme weather events had a significant effect on US banks' performance (Blickle et al. 2021).

For these reasons, economists have long been reluctant to endorse attempts to “stop” climate change or even aggressively reduce GHG emissions because the costs would not be worth it. As one critic of the economics of climate policy put it:

Mainstream climate economics takes global warming seriously, but perplexingly concludes that the optimal economic policy is to almost do nothing about it... The contrast is striking. While climate science is sending out loud-and-clear messages that fossil-fuel disinvestment must start now, letting go of coal and oil and diverting resources into renewable energy technology systems, to keep warming below the 2°C limit (IPCC 2014), mainstream climate economics claims that overly ambitious climate targets will unnecessarily hurt the economy and immediate de-carbonization is too expensive. Most climate economists thus recommend humanity to just wait-and-see.

(Storm 2017)

The mainstream economics position on the climate policy question is best represented by the findings over the past three decades from Integrated Assessment Models (IAMs) of climate change policy, for which Yale economist William Nordhaus was awarded the 2018 Nobel Memorial Prize in economics. IAMs combine economic, climate, and social data into a unified framework for simulating climate damages and evaluating the optimal policy response (Resources for the Future 2025). Nordhaus' work has generally supported modest global climate policy, with aggressive measures largely deferred to later in the century. Nordhaus developed the so-called Dynamic Integrated Model of the Climate and Economy model, or DICE, in the early 1990s (Nordhaus 1993) to study the interaction between climate change, climate policy, and global economic growth over long times. DICE assumes global emission control can be coordinated at no cost and asks what the optimal policy target should be. The climate component of the DICE model is based on simplified climatological modeling. The version of DICE at the

time of Nordhaus' Nobel Prize award was described in Nordhaus (2018); it had a climate sensitivity parameter of 3.1°C for CO₂ doubling, consistent with the best estimate in contemporary IPCC reports (3.0°C).

The baseline (no policy) scenario incurs only \$0.4T in global abatement costs and leads to \$134.2T (trillion dollars) in global climate damages for a total cost of \$134.6T. The climate model component of DICE projects 4.1°C warming by 2100 relative to preindustrial temperatures. Note that this is a higher estimate of warming than many IPCC climate models. (AR6 offers 2.7°C in 2100 under a moderate emissions scenario.)

The Optimal Policy scenario barely deviates from the business-as-usual path. It aims for +3.5°C warming, in other words we scale back only the lowest-value fossil fuel use and otherwise just live with almost all the warming. This suggests that most CO₂ emissions are less harmful than the policies that would be necessary to abate them. Trying to prevent warming causes costs quickly to outstrip the benefits. Pursuing a goal of capping warming at 2.5°C creates total costs of \$177.8T, which is \$43.2T worse than doing nothing at all. Nordhaus didn't evaluate trying to reach a Paris-type target of 1.5°C warming but it would be even worse.

A subsequent edition of DICE includes higher assumed damages from warming which, not surprisingly leads to more aggressive policy recommendations, as explained in the section below on the Social Cost of Carbon.

13.1.2 Empirical analysis of climate change and economic growth

Many other studies have used econometric methods instead of IAMs to look at the potential impact of climate change on economic growth. Dell et al. (2012, herein DJO12) was an influential study that used a multi-country panel of national-level data spanning 1950 to 2005, in which they matched climate and economic data by averaging temperature from the local grid cell level up to the national level using population weights. They found that warming yields an insignificant positive effect on income growth in rich countries but a significant negative effect in poor countries. Moore and Diaz (2015) modified the DICE model to take that finding into account and concluded that it implied a dramatically higher Social Cost of Carbon due to the compounding effects of income loss over time.

A large subsequent literature has debated the robustness of the DJO12 findings. Burke et al. (2015) analyzed a global panel with temperatures averaged up to the national level and found a negative effect on growth from warming in rich and poor countries alike when the national average temperature is above 13°C. Zhao et al. (2018) used the G-Econ data set of Nordhaus (2006), which breaks economic activity down to the grid cell level, replicated DJO12-type results on the same subset of countries as used in DJO12 but then showed that on the full global sample warming increases growth in rich countries and poor countries alike, though the positive effect in the latter group is confined to where local temperatures are below about 16°C. Greßer et al. (2021) developed a regional economic data set for 1,542 sub-national regions around the world between 2005 and 2015 and found temperature had no effect on growth. Yang et al. (2023) updated the DJO12 data set and applied an estimator robust to

mixed sample frequencies, finding that while temperature shocks exerted a temporary effect on income levels, they did not have a significant lasting effect on growth rates.

Newell et al. (2021) noted that there is no underlying theory to guide econometric model specification in this literature. Taking into account the arbitrary choices of which explanatory variables to include they identified over 800 possible model specifications. Using the Burke et al. (2015) data they used an estimation method that accounts for model uncertainty and found that the model form preferred by Burke et al. (2015), which implied negative effects of warming on growth even in rich countries, is explicitly excluded by the optimal model selection algorithm. Overall they could not detect a temperature effect on GDP or GDP growth, and they estimated the 95% confidence interval for the impact on global growth as of 2100 even under the exaggerated RCP8.5 warming scenario spans -86 percent to +388 percent. In other words the net effect is likely positive but too uncertain to distinguish from zero.

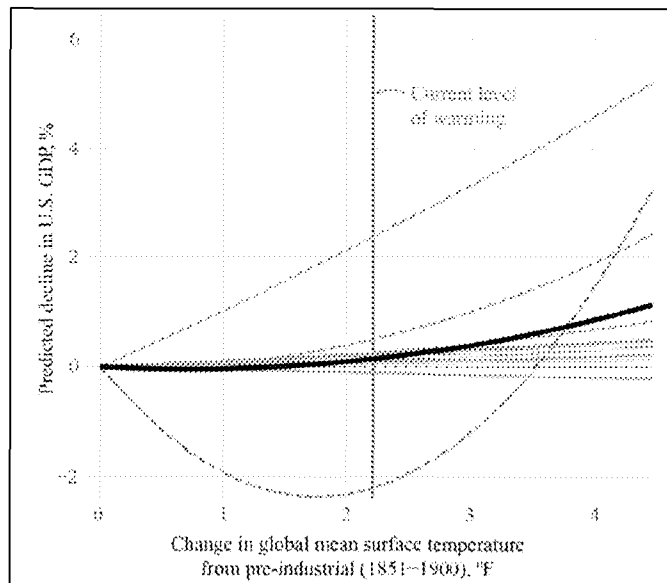
Barker (2023) criticized the DJO12 assumption that countries can be grouped into fixed “poor” and “rich” categories based on their incomes many decades ago. He noted that many countries were once poor but became rich over time, and if this is considered the original temperature effects reported by Dell et al. became small and insignificant.

Berg et al. (2023) argued that countries shouldn’t be grouped into large Rich/Poor categories because they are too heterogeneous. They instead estimated country-specific temperature response coefficients then grouped countries with similar response coefficients into small panels. They separately estimated responses to global and idiosyncratic local temperature shocks to better identify the climate signal in weather data. Overall they found countries experiencing negative effects of warming on growth outnumbered those experiencing positive effects, but only temporarily: eventually the effects reverse such that about twice as many countries experience a net positive growth effect. They also found global (as opposed to local) temperature changes are much more likely to benefit growth in poor countries than rich ones. In a simulation to 2100 even using the extreme RCP8.5 scenario they computed the average global GDP loss would be only 1.9% compared to a scenario with no warming. That is, instead of the economy growing 400% it would grow 398%. The implication of Nordhaus’ analysis is that trying to prevent the warming would lead to far less than 398% growth.

To summarize, economists have long considered climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in the Fifth Assessment Report. Mainstream climate economics has recognized that CO₂-induced warming may have some negative economic effects but they are too small to justify aggressive abatement policy, and trying to “stop” or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries but it has subsequently been found not to be robust. Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit from it as rich countries.

The expectation that significant global warming would have a small impact on the U.S. economy was acknowledged quietly by the Biden Administration, even as the President was proclaiming a climate emergency. The following figure, from a 2023 OMB-CEA [report](#), shows the expected decrement in U.S.

GDP as a function of temperature rise. The colored lines show the results of a dozen peer-reviewed published studies while the solid black line is their average. The figure could be summarized as “a few percent impact for a few degrees of warming”. Given that the economy’s annual growth rate is expected to be 1-2 percent, the impact of a warming globe is indeed negligible.



Need caption

13.2. Models of the Social Cost of Carbon

The Social Cost of Carbon (SCC) is a tool for quantifying the economic impact of carbon dioxide emissions, helping policymakers weigh the costs and benefits of climate policies. It estimates the damage caused by emitting one additional ton of CO₂, expressed in dollars. More formally, the SCC is the discounted present value of the current and future marginal loss of economic welfare due to an additional ton of CO₂ entering the atmosphere. On its own the SCC is not the appropriate price to attach to CO₂ emissions for the purpose of optimal emissions control but it can be converted into an optimal tax rate by scaling it by the Marginal Cost of Public Funds (MCPF). The theory behind this was first derived by Sandmo (1975) and has been reiterated many times since then by other economists working on the topic (e.g. Parry et al. 1999). The MCPF is the cost in terms of lost private economic welfare of raising public revenue by one dollar and always exceeds unity. If a jurisdiction does not use a carbon tax, this formula still indicates the upper bound on the amount emitters should spend on abatement options at the margin along the optimal policy path. Regulations should be imposed only insofar as they do not impose marginal abatement costs in excess of the optimal tax rate.

13.1.2 Estimating the SCC

Although the literature refers to “estimates” of the SCC, it is not estimated in the way other economic statistics are estimated. For instance, data on market transactions including prices and quantities can be used to estimate the current inflation rate or the growth rate of per capita real Gross Domestic Product, and there are well-understood uncertainties associated with these quantities. But there are no market data available to measure many if not most of the marginal damages or benefits believed to be associated with CO₂ emissions, so these need to be imputed using economic models.

For example, an influential component of some SCC calculations is the perceived social cost associated with changed risk of future mortality due to extreme weather. There is no market in which people can directly attach a price to that risk. At best economists can try to infer such values by looking at transactions in related markets such as real estate or insurance, but isolating the component of price changes attributable to atmospheric CO₂ levels is very difficult.

Economists use IAMs to compute the SCC. Two of the best known IAMs are the Climate Framework for Uncertainty, Negotiation and Distribution (“FUND”, Tol 1997) and Nordaus’ DICE. IAMs embed a stylized global climate model with a very simplified representation of the global economy, including a “damage function” or set of functions relating ambient temperature to local economic conditions. The assumptions embedded in the damage function will largely determine the resulting SCC.

One approach to developing a damage function is to begin with estimates of the costs (or benefits) of warming in specific sectors in countries around the world and aggregate up to a global amount. This was the approach used in FUND. An alternative approach is to develop a simple equation that penalizes global income according to a simple quadratic function of the average global temperature. This approach was used in DICE. In the case of the FUND model many hundreds of parameters had to be selected, whereas in DICE only three were needed and were originally chosen to assign a predetermined penalty (1.2%) to global output as of 3°C warming, with a quadratic term implying that damages grow with the square of the global average temperature anomaly. Barrage and Nordhaus (2024) recently changed the parameters to increase the penalty at 3°C to 1.6%, and added a discrete additional 1.0% GDP penalty at 3°C warming to account for “tipping points” (discrete large-scale environmental changes triggered by crossing a warming threshold) and a “judgmental adjustment” of 0.5% for excluded impacts at 3°C warming. Not surprisingly the newer version of DICE generates much higher SCC estimates than before.

The concepts of estimation and uncertainty do not readily apply to SCC calculations. By comparison, the question of whether precipitation has trended up or down along the South Carolina coast for the past hundred years can be addressed by collecting rainfall data, estimating a trend parameter and calculating statistical confidence intervals using methods with well-understood mathematical properties. In this way uncertainty can, in principle, be resolved by collecting more data and applying more accurate methods. But no amount of data collection can change the fact that many components of the SCC are unknown and rely on judgment and opinion based on knowledge of the underlying literature on the physical effects of climate change.

SCC calculations are thus best thought of as “if-then” statements: *if* the following assumptions hold, *then* the SCC is \$X per tonne. The list of ‘if’ statements includes the premise that the world’s climate and economy work according to the representation in the IAM. One way this may fail to hold is in the timing of warming. Every IAM assumes a value of the Equilibrium Climate Sensitivity (ECS), controls the amount of warming that results from CO₂ emissions and can be freely varied for the purpose of generating a distribution of SCC values associated with uncertainties over ECS. But as Roe and Baumann (2013)

pointed out, time-to-equilibrium increases with the square of ECS, so an upward adjustment of the ECS parameter without an appropriate slowing down of the adjustment process can yield distorted present value damage estimates. In particular, the upper tail of warming associated with some commonly-used ECS distributions is physically impossible for even a thousand years into the future (Roe and Baumann 2013) yet in an IAM would be realized within a couple of centuries. Failure to align ECS with time-to-equilibrium will lead to an overestimate of the SCC value.

13.2.2 Variations in the SCC

Every level of the IAM calculation includes assumptions, some more influential than others. Key assumptions include the following.

- The discount rate: Climate damages accrue over a long time horizon, and costs a century or two in the future need to be discounted to the present. The higher the discount rate the smaller the present value of future damages and vice versa. The discount rate represents the opportunity cost of spending money today rather than investing it and then having more to spend tomorrow. Some economists have argued for the use of very low discount rates in SCC calculations, resulting in policy recommendations that favor relatively large immediate investments in CO₂ emission reductions. The downside is that other investments could potentially earn a larger rate of return for society.
- Equilibrium Climate Sensitivity: IAMs have customarily employed a value of 3.0°C or 3.1°C following the IPCC's guidance. Empirically-estimated ECS values tend to be lower than this (see Chapter XX). Dayaratna et al. (2017, 2020, 2023) have shown that use of lower empirically-derived ECS values dramatically lower the resulting SCC estimate, even when low discount rates are used.
- Damage function coefficients: IAMs assume CO₂ and warming cause net harms that increase exponentially with temperature. More recently, IAMs have also incorporated effects from assumed potential climate tipping points. The FUND model took limited but explicit account of CO₂ fertilization effects in agriculture. Since the coefficients were selected prior the publication of the current evidence of global greening and the magnitude of benefits to crops from elevated CO₂ (see Chapters 2 and 10) the growth effects are likely understated. The DICE model (and others) did not explicitly include any CO₂ fertilization benefit, except to the extent it was taken into account in the literature consulted when picking the damage function coefficients. The damage function in FUND contains a region in which low warming yields net benefits in many regions, a finding which is supported by econometric models of warming and growth (Berg et al. 2023) and econometric simulations of agricultural changes (McKittrick 2025). The DICE damage function, by construction, rules out net benefits at any warming level.
- Emission scenarios: IAMs generate SCC estimates that increase as the pre-existing concentration of CO₂ increases. Consequently the value of damages later in the century will be higher, depending on the assumed baseline emissions over the coming decades.
- Abatement costs: IAMs represent the cost to the economy of reducing CO₂ emissions. If CO₂ emission reductions are assumed to be inexpensive, then the model will conclude that the optimal policy should aim for deeper emission cuts and vice versa.

It is informative to ascertain whether SCC results are invariant to changes in some assumptions. But when different assumptions result in higher or lower SCC values, the change in the SCC value does not provide *prima facie* evidence about the validity of the assumptions. For example, in 2023 the US Environmental Protection Agency raised its preferred SCC value about 5-fold over the estimates it had issued ten years earlier. This is not because new data had been collected or better mathematical methods had been invented, but because new assumptions had been used, and the validity of those assumptions was a separate question. One was that global agricultural damages were far higher than previously assumed, based on an analysis in Moore et al. (2017). But as discussed in Section XX, McKittrick (2025) showed that Moore et al. (2017) had used a database in which half the CO₂ change observations were missing. When as many of those observations as possible were recovered from underlying sources and the analysis was rerun, the projected crop yield losses disappeared and turned into gains at all warming levels. Hence the portion of the EPA's SCC revision attributable to agricultural yield losses was unwarranted.

13.2.3 Evidence for low SCC

Chapter 2 reviewed evidence on climate change and greening, and Chapter 10 looked at climate change and US agriculture. Evidence shows that CO₂ fertilization has a stronger beneficial effect on agriculture than was known at the time that IAMs like DICE and FUND were parameterized. In particular Haverd et al. (2020) found the observed CO₂ fertilization rate has been almost double what had been predicted by crop models. Dayaratna et al. (2023) used the updated empirical ECS distribution estimate of Lewis (2022), which assimilates modern instrumental and paleoclimatic temperature records, and allowed for a 30 percent gain in the CO₂ fertilization benefit in the FUND model, and found that, even at a low discount rate of 2.5 percent, the median SCC as of 2050 is only \$18.67, with a 24 percent probability of the true value being negative. At a five percent discount rate the median SCC value is negative until the mid-2040s and at 2050 was only \$0.37 with a 49 percent probability of being negative. Thus, under reasonable assumptions a mainstream IAM using updated scientific inputs yields evidence consistent with the SCC not being significantly greater than zero.

It should also be noted that the SCC is focused on the social costs of CO₂ emissions from fossil fuel use. It does not measure the private marginal benefits to consumers and society from the availability of fossil fuels. Public willingness to pay for fuels of all types indicates the value to society of reliable, abundant fossil energy. Tol (2017) estimates that the private benefit of carbon is large relative to the social cost. This can be illustrated by noting that the price of a gallon of gas indicates the marginal value to the consumer of the fuel. Suppose we assume a relatively high Social Cost of Carbon of, say, \$75 per tonne. Deflated by a MCPF value of 1.5 that would result in a carbon tax of \$50 per tonne, which equates to about 44 cents per gallon of gas (Lavelle 2019). A pre-tax price of \$3.00 per gallon would imply the marginal social benefit of the fuel is nearly seven times the marginal social cost.

13.3. Summary

It is increasingly being argued that the SCC is too variable to be useful for policymakers. Cambridge Econometrics (Thoung 2017) stated it's "time to kill it" due to uncertainties. The UK and EU no longer use SCC for policy appraisal, opting for "target-consistent" carbon pricing (UK Department for Energy Security and Net Zero 2022, Dunne 2017). However the weaknesses of the SCC concept don't mean that other regulatory measures are inherently better or more efficient. Many climate regulations (such as electric vehicle mandates, renewable energy mandates, energy efficiency regulations and bans on certain types of home appliances) end up costing far more per tonne of abatement than a simple price on carbon emissions.

In summary, SCC estimates are highly uncertain due to unknowns in future economic growth, socioeconomic pathways, discount rates, climate damages, and system responses. The SCC is not intrinsically informative as to the economic or societal impacts of climate change. It provides an index connecting large networks of assumptions about the climate and the economy to a dollar value. Some assumptions yield a high SCC and others yield a low or negative SCC. The evidence for or against the underlying assumptions needs to be established independently; the resulting SCC adds no additional information about the validity of those assumptions.

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14. U.S. Vehicle-Based CO₂ Emissions and the Global Climate

The EPA's 2009 Endangerment Finding focused on CO₂ emissions from cars and light-duty trucks in the U.S. because Section 202(a) of Clean Air Act mandates the EPA to set emissions standards for motor vehicles if pollutants are found to endanger public health or welfare. Thus, the 2009 Endangerment Finding obligated the EPA to regulate emissions from new motor vehicles.

Two questions that naturally arise are: (1) How large a reduction in CO₂ emissions would result from such regulation? and (2) What would be the climate impact of such regulation?

The first question can be addressed using CO₂ emissions statistics from the EPA and the International Energy Agency (IEA). The second question can be addressed by the fact that the reduction in global warming is proportional to how much global emissions are reduced, keeping in mind that how much the CO₂ content of the atmosphere increases in any given year is the result of total global CO₂ emissions, not just U.S. emissions.

In 2022, the emissions from U.S. cars and light duty trucks totaled 1.03 billion metric tons of carbon dioxide (GtCO₂). This is only 2.8% of the 36.8 GtCO₂ of global energy-related emissions in 2022. If we were to take into account emissions from land use and cement production, that fraction would be even smaller, but for the purpose of the following calculation, it will suffice.

Even if all CO₂ emissions were eliminated from U.S. cars and light duty trucks in 2022, the impact on global warming would be less than 3%. Would such a tiny impact even be measurable in global temperature data? For the period 1979-2023, which has the most extensive global coverage of a variety of weather data types, warming trends from five global temperature datasets range from +0.163 deg. C per decade from the NCEP/NCAR R1 reanalysis dataset to +0.211 deg. C per decade for the ERA5 reanalysis dataset. The latter estimate is 29% larger than the former, indicating that a 3% reduction in the rate of global warming from eliminating U.S. vehicle CO₂ emissions would be an order of magnitude below the threshold of measurability. Given that global-average temperature is the most robust climate change metric, this means any other climate impacts (e.g. severe weather, floods, drought, etc.) from the elimination of U.S. vehicle CO₂ emissions would be even less significant.

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16. Glossary of Terms

2XCO₂: doubling of the atmospheric CO₂ content relative to pre-Industrial times, a commonly used baseline for addressing climate change. In 2025, atmospheric CO₂ concentrations were approximately 50% of the way to 2XCO₂.

ABATEMENT: in the context of pollution, the reduction of harmful impacts through pollution reductions

ACE (Accumulated Cyclone Energy): a statistical measure of a tropical cyclone's energy accumulated over its lifetime, calculated from a summation of the square of maximum sustained wind speeds

ACIDIFICATION: a commonly used term for the reduction in ocean pH from more alkaline to less alkaline values

AEROSOLS: tiny solid or liquid particles suspended in the air

ALKALINE: having a chemical pH greater than 7.0. The "opposite" of acidic, which means a pH less than 7.0

AMBIENT: relating to the immediate surroundings of something

ANTHROPOGENIC: created by humans

AR (IPCC Assessment Reports): periodic assessments published by the IPCC evaluating current knowledge of the climate system, global change, and associated issues. The most recent was AR6 in 2023.

BIOMASS: the total quantity or weight of organic matter in a given area or volume

CARBON: popular and widely used shorthand term for carbon dioxide

CMIP (Coupled Model Intercomparison Project): The IPCC's organized effort to compare many different global ocean-atmosphere climate models when they are all forced with the same emissions scenario(s)

CONUS: the contiguous 48 U.S. states

DICE (Dynamic Integrated model of the Climate and Economy): An Integrated Assessment Model (IAM) developed by William Nordhaus in 1993.

DISCOUNT RATE: here, the rate used to convert future costs and benefits of environmental regulations into their present value. A high discount rate reduces the present value of future environmental benefits from regulating sooner; a low discount rate favors long-term benefits of regulating sooner.

DRY ICE: frozen carbon dioxide

ECONOMETRICS: the branch of economics concerned with the use of math and statistics in describing economic systems

ECS (Equilibrium Climate Sensitivity): The total amount of eventual global-average surface warming in response to a hypothetical doubling of the atmospheric CO₂ concentration compared to pre-Industrial levels.

EL NIÑO: the warm phase of ENSO, involving weaker upwelling of cold water off the South American coast and weaker Pacific trade winds.

EMISSIONS SCENARIO: An assumed scenario of future greenhouse gas emissions (or resulting atmospheric concentrations) based upon assumptions regarding global economic activity, the prevalence of fossil fuel use, and (sometimes) global carbon cycle model estimates of the rate of CO₂ uptake by land and ocean.

ENDANGERMENT FINDING (EF): the 2009 finding by the Administrator of the EPA that CO₂ emissions endanger human health and welfare

ENSO: El Niño – Southern Oscillation, a prominent natural climate fluctuation involving year-to-year variations in the upwelling of cold water off the equatorial coast of South America and associated strengthening or weakening of trade winds across the Pacific Ocean

FACE: (Free-Air CO₂ Enrichment) large-scale open-air studies that expose plants to elevated CO₂ levels, simulating future climate scenarios.

FOSSIL FUEL: a natural fuel such as coal or natural gas formed in the geological past from the remains of living organisms

FUND: An Integrated Assessment Model (IAM) developed by Richard Tol in 1997.

GBR (Great Barrier Reef): the world's largest coral reef ecosystem located off the northeast coast of Australia

GDP (Gross Domestic Product): total market value of all the final goods and services produced within a country's border, usually over one year

GHCN: the Global Historical Climatology Network, consisting of a time-varying number of globally distributed weather stations making hourly, daily, or monthly measurements of precipitation, temperature and sometimes snowfall and snow depth.

GLOBAL GREENING: the satellite-observed increase in greenness in most vegetated land areas observed since the early 1980s

GNP (Gross National Product): total market value of all the final goods and services produced by the citizens a country, usually over one year

GREENHOUSE EFFECT (GHE): the tendency for any planetary atmosphere containing greenhouse gases to be warmer in the lowest layers than if those gases did not exist.

GREENHOUSE GAS (GHG): an atmospheric gas that absorbs and emits infrared (IR) radiation, especially water vapor, CO₂, and methane.

HURST PHENOMENON: see long term persistence.

HYDROLOGY: the study of the movement of water, especially on land and the atmosphere

IAM (Integrated Assessment Model): a computerized tool that combines economics, climate science, and social sciences to provide quantitative relationships between human and Earth systems, helping to inform policy decisions

IEA: International Energy Agency

IPCC (Intergovernmental Panel on Climate Change): A panel of international experts and governmental representatives established by the United Nations and World Meteorological Organization in 1988 to provide governments at all levels with scientific information that they can use to develop climate policies

IR (Infrared): heat radiation that all solid objects and greenhouse gases emit by virtue of their temperature.

LA NIÑA: the cool phase of ENSO, involving stronger upwelling of cold water off the South American coast and stronger Pacific trade winds.

LONG TERM PERSISTENCE (LTP, or HURST PHENOMENON): the tendency for natural systems such as precipitation, droughts, and floods to have persisting behavior over time, as opposed to random behavior, which impacts our interpretation of long-term trends in climate data

MAIZE: corn

MODEL: a computer code or collection of codes which quantify our knowledge of various processes and the interactions between those processes

MORTALITY: death or number of deaths, usually expressed for a specific population and period

NCA (National Climate Assessment): A periodic report mandated by the Global Change Research Act of 1990 summarizing the impact of climate change on the United States> There have been five NCA reports: NCA1 (2000), NCA2 (2009), NCA3 (2014), NCA4 (2017-18), and NCA5 (2023)

OECD (Organization for Economic Cooperation and Development): a specific list of 38 countries having a democratic system of government and free economic systems

PALEOCLIMATE: climate of the distant past, before modern weather instruments were widely used (typically pre-1850), necessitating the use of “proxy” measurements such as tree rings, ice core, pollen records, etc.

PDI (Power Dissipation Index): a statistical estimate of the accumulated destructive potential of a tropical cyclone over time, calculated as a summation of the cube of the maximum sustained wind speeds

PHOTOSYNTHESIS: the process by which plants grow, requiring carbon dioxide, water, and light at sufficiently warm temperatures (10 to 35 deg. C for optimal function)

PPM: parts per million, a measure of the concentration of a substance in (for example) the atmosphere

PRE-INDUSTRIAL: the historical period before which human greenhouse gas emissions were considered significant, usually assumed to be the mid-1700s

RADIATIVE FEEDBACK: a change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in surface temperature

RADIATIVE FORCING: the change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in greenhouse gases, anthropogenic aerosols, volcanoes, etc.

RCP SCENARIOS: Representative Concentration Pathways, different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC's Fifth Assessment Report (AR5). RCP scenarios have a number label (e.g. RCP6.0) indicating how much radiative forcing they assume in 2100 relative to pre-Industrial times, in Watts per sq. meter. RCP4.5 and RCP6.0 are intermediate scenarios, whereas RCP8.5 is an extreme scenario with very large future emissions of greenhouse gases.

RICARDIAN ANALYSIS: a method used in environmental economics to estimate the economic impacts of climate change, particularly on agriculture

SOCIAL COST OF CARBON (SCC): an estimate of the total economic damages, measured in dollars, caused by emitting one additional ton of CO₂ into the atmosphere

SSP SCENARIOS: Shared Socioeconomic Pathways, different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC's Sixth Assessment Report (AR6). Some of the SSP scenarios are analogous to the older RCP scenarios, for purposes of continuity and comparison to earlier climate model assessments.

TC: tropical cyclone

TMAX: the daily maximum surface air temperature

TMIN: the daily minimum surface air temperature

TOA: top of atmosphere

TOXICOLOGY: the study of the adverse effects of chemical substances on living organisms.

TREND: usually, the linear regression slope fit to a time series of data, one of the most commonly used metrics to describe climate change over a long period of time

UHI (Urban Heat Island): the tendency for inhabited areas to be warmer than their rural surroundings, due to the replacement of natural land and vegetation with roads, parking lots, buildings, and waste heat sources.

USHCN: the U.S. Historical Climatology Network, consisting of quality-controlled temperature and precipitation data from 1,218 surface weather stations

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1 Carbon dioxide as distinct from criteria air contaminants

This report is chiefly concerned with carbon dioxide (CO₂) emissions from fossil fuel use. Although it has become common to refer to CO₂ as “pollution” this is a misnomer. In the framework of United States clean air policy there are six types of so-called Criteria Air Contaminants (EPA, undated): particulate matter, ground-level ozone, Sulfur Dioxide, Nitrogen Dioxide, Lead and carbon monoxide (CO). Air contaminants are subject to regulatory control because they cause local problems depending on concentrations that include nuisances (odor, visibility problems), damage to plants and, at high enough exposure levels, toxicological effects in humans.

CO₂ has not historically been viewed as an air pollutant in the US or elsewhere because it is odorless, does not affect visibility and has no toxicological effects at ambient levels. It is a naturally-occurring part of the atmosphere and a key component of human and plant respiration. CO₂ is essential for plant photosynthesis and higher levels are generally considered beneficial for vegetation, as will be discussed in this report.

Ambient outdoor air contains about 420 parts per million (ppm) CO₂. The US Occupational Safety and Health Administration issues guidelines for indoor workplaces in which elevated CO₂ may be encountered, such as where dry ice is used. The Permissible Exposure Limit is 5,000 ppm over 8 hours (OSHA 2024). Allen et al. (2015) reported evidence of diminished performance on some cognitive tasks among workers in office cubicles when exposed to CO₂ levels above 1,000-1,500 ppm.

The main concern about CO₂ is its potential effects on the global climate. This is a very complex question which will occupy much of this report. We will begin in the next section by looking at the role of CO₂ in promoting global greening and agricultural productivity growth, then we will examine the effect of CO₂ on ocean alkalinity. We then turn to CO₂'s role as a so-called greenhouse gas (GHG), beginning with a brief description of radiative forcing, the carbon cycle and the role of aerosols. Part II of this report discusses in detail the topic of the climatic response to GHGs. Part III discusses some aspects of the impacts of climate change on ecosystems and society.

US Environmental Protection Agency (Undated) Criteria Air Pollutants. <https://www.epa.gov/criteria-air-pollutants> accessed April 29 2025.

US Occupational Health and Safety Administration (2024) “OSHA Occupational Chemical Database: Carbon Dioxide” <https://www.osha.gov/chemicaldata/183>

Allen, Joseph G, Piers MacNaughton, Usha Satish, Suresh Santanam, Jose Vallarino and John D.S. Spengler (2015) Associations of Cognitive Function Scores with Carbon Dioxide, Ventilation, and Volatile Organic Compound Exposures in Office Workers: A Controlled Exposure Study of Green and Conventional Office Environments. *Environmental Health Perspectives* 124(6) pp. 805-812 <https://doi.org/10.1289/ehp.1510037>

2 CO₂ fertilization and global greening

MOVED SECTION

2.1 CO₂ and global greening

“Greening” refers to an increase in the total amount of the Earth’s surface covered in plants. The main measure of greening is “Leaf Area Index” or LAI as measured by satellite. Many studies over the past decade have confirmed a global greening pattern (rising LAI) attributable to rising CO₂ levels. Zhu et al. (2016) was one of the first studies to report that global greening was detectable from space using satellite sensors. On data spanning 1982 to 2011 they detected greening over 25-50% of the Earth versus browning over only 4%, and they attributed 70% of the greening to rising CO₂ levels (see Figure 2.3).

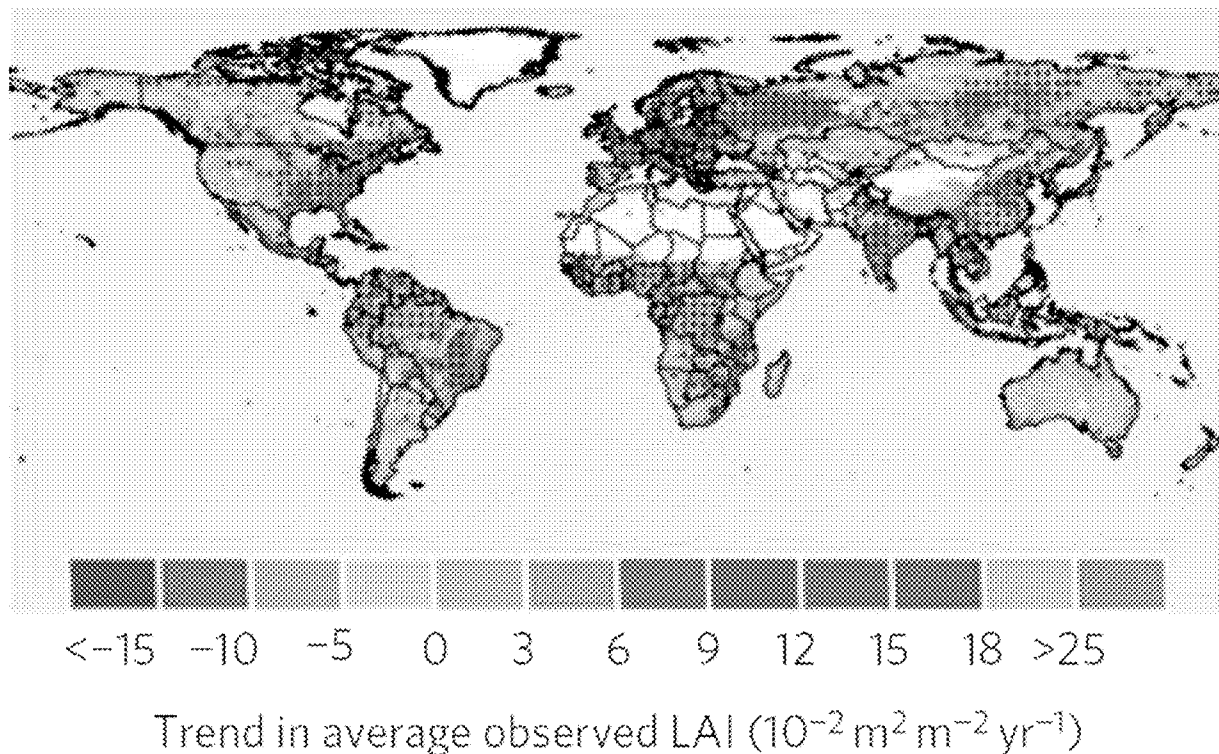


Figure 2.3: Trends in average Leaf Area Index (LAI). Source: Zhu et al. 2016 Figure 3.

Zheng (2017) confirmed the pattern, noting that greening over 30 years had added 8% to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen et al. (2019) noted that China and India were taking particular advantage of it though land management changes. Thus while China accounts for only 6.6% of global vegetated area it accounts for 25% of global net increase in LAI. Piao et al. (2020) noted that greening was even observable in the Arctic.

While plant models predict increases in photosynthesis should be observed in response to rising CO₂, Haverd et al. (2020) reported that observed CO₂ fertilization rate was nearly double what models had predicted. That is, CO₂ fertilization had driven an increase in observed global photosynthesis by 30% since 1900, versus 17% predicted by plant models. Among other things this indicates that global models of the socioeconomic impacts of climate change have likely understated the benefits to crops

and agriculture from rising CO₂. The connection between CO₂ fertilization and climate policy will be discussed in Chapter XX.

Finally, Chen et al. surveyed claims that greening had slowed down since 2000 due to drought stress. They found instead that claims of slowed greening could be attributed to faulty satellite sensors. Once the data were corrected they found greening was accelerating over 55% of the world while browning was accelerating over only 7% of the world. Overall the greening trend was continuing with no evidence of slowdown, and CO₂ fertilization remained the dominant driver

2.2 Photosynthesis and CO₂ levels

A key direct effect of adding CO₂ to the atmosphere is its positive effect on plant life via enhancement of photosynthesis and improvement to plant water use efficiency.

The term *photosynthesis* describes the process by which plants build biomass. The process requires carbon dioxide (CO₂), water (H₂O), and light. The plant enzyme responsible for photosynthesis is called Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO₂ is available at the surface of the RuBisCo enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass, which is referred to as the C3 process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth’s atmospheric CO₂ levels were usually much higher than they are today. About 400 million years ago CO₂ levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Bernier 2006, Judd et al. 2024). Over the past 35 million years the level of atmospheric CO₂ has been steadily declining. During glaciations levels have fallen as low as 170 ppm (Gerhart and Ward 2010). In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C4, in which CO₂ is concentrated in the vicinity of Rubisco allowing for the C3 process to function more efficiently. For agricultural purposes the plant categories are:

- C3: rice, wheat, soybeans and most other crops
- C4: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth rates would have declined and eventually ceased. Below 180 ppm many C3 species experience growth rate reductions on the order of 40-60% compared to their growth rates at 350 ppm (Gerhart and Ward 2010). C3 plants have been observed under experimental conditions to stop growing altogether at levels between 60—140 ppm CO₂. Some C4 plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Currently, CO₂ levels are about 420 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 1 which is reproduced from Gerhart and Ward (2010). It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains exhibited from increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

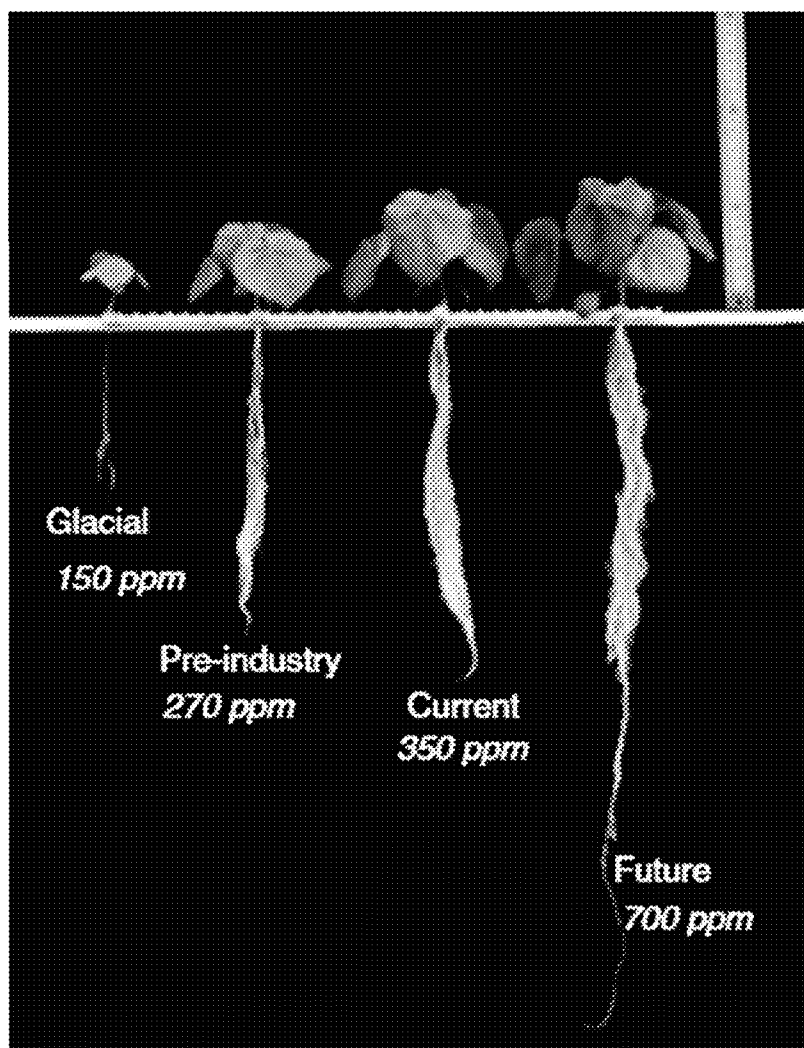


Figure 2.1: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010).

Over the past 60+ years there have been tens of thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C3 plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, which allows water to evaporate away. Under enriched CO₂ conditions the stomata are closed for longer periods helping the plant retain water longer, thereby increasing water use efficiency.

One of the ways in which scientists have studied the effects of CO₂ enrichment is through “free air enrichment experiment” or FACE plots, in which small chimneys are placed in fields surrounding plants and the growth response to elevated CO₂ under varying weather conditions are recorded. Ainsworth and Long (2021) summarize results from about 250 such studies. They conclude:

- “Across 186 independent studies of 18 C3 crops, elevation of [CO₂] by ca. 200 ppm caused a ca. 18% increase in yield under non-stress conditions.”
- “Legumes and root crops showed a greater increase and cereals less. Nitrogen deficiency reduced the average increase to 10%, as did warming by ca. 2°C.”

The authors reported that C4 plants mainly exhibited benefits during drought conditions. However additional evidence on corn growth under enhanced CO₂ levels will be provided below.

2.2 CO₂ and key global food crops - I DON'T THINK THIS SECTION IS NEEDED

Rice

Lv (2020) analyzed experimental studies done on conventional rice plants in Japan and China. They found that the type of cultivar was a determining factor in quantifying the amount of response displayed, but all cultivar types showed positive yield response to elevated CO₂ levels. An additional 200 ppm CO₂ raised rice yields by 13.5%-32.8% for three common rice cultivars. A similar meta-analysis synthesis (Hu, 2021) was done for all available FACE studies on rice. On average, elevated CO₂ enhanced rice yields by 16.2% and improved their leaf photosynthesis. Hybrid rice displayed a greater yield enhancement (24.7%) than conventional rice (14.2%). The synthesis also revealed that yield response to elevated CO₂ was constrained by changes in nitrogen availability and temperatures. Ainsworth and Long (2021) argued that if farmers are careful in choosing the rice variety with the highest yield potential, they will show as much as 35% yield increase from an extra 200 ppm CO₂ compared to 14% without adaptation.

Potatoes

Lee (2020) grew potato plants under elevated CO₂ concentration and reported they “yielded a distinct increase in growth and development and canopy net photosynthetic rate during tuber initiation and bulking. Consequently, biomass and canopy net photosynthesis increased, and tuber yield increased by 20.3%. The CO₂Science.org website reports on 33 published experiments between 1988 and 2019 exposing potatoes to enriched CO₂ levels. Converted to a common +300ppm scale the average photosynthesis rate change was +50.3 percent.

Soybean

Studies on the impact of elevated CO₂ on Soybean (*Glycine max* (L.) Merr.) plants in the water-deficient region of Huang-Huai-Hai Plain, China, showed that elevated CO₂ concentrations resulted in improved photosynthesis rate, water use efficiency and growth (Li, 2013) under both normal conditions and drought conditions. The CO₂Science.org website reports on 108 published experiments between 1985 and 2019 exposing soybean to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +50.9 percent. In addition there were 10 studies reporting on +600 ppm CO₂ enrichment, resulting in an average increase in photosynthesis of 90.3%.

Maize (corn)

The CO₂Science.org website reports on 28 published experiments between 1983 and 2018 exposing corn (*Zea mays* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +23.7 percent. Corn also benefits from increased drought tolerance under elevated CO₂. An experimental study (Allen Jr, 2011) exposed plants to water stress conditions in sunlit controlled-

environment chambers at 360 ppm (ambient) and 720 ppm (elevated) CO₂. The drought stress caused a 41% loss of growth under ambient CO₂ but only a 13% loss under elevated CO₂.

Wheat

The CO2Science.org website reports on 92 published experiments between 1983 and 2020 exposing common wheat (*Triticum aestivum* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +67.6 percent. Blandino (2020) measured the yield as well as nutritional quality of an “improver” hybrid wheat variety and its parents under elevated CO₂ levels (+166 ppm). They reported a grain yield increase of +16% but a 7% decrease in grain protein levels. But they found that the food quality of different wheat varieties responded differently to elevated CO₂ levels, so that with proper varietal selection end-users can select wheat types that best take advantage of the elevated CO₂.

Coffee

The CO2Science.org website reports on 18 published experiments between 2013 and 2020 exposing coffee (*Coffea arabica*) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +110.9 percent. To forecast the future impact of climate on coffee yields, Verhage (2017) analyzed yield data over 1989 to 2013 from 42 municipalities in Brazil. The study found that “yield losses due to high air temperatures and water deficit will increase, while losses due to frost will decrease. Nevertheless, extra losses are offset by the CO₂ fertilization effect, resulting in a net increase of the average Brazilian Arabica coffee yield of 0.8% to 1.48 t ha⁻¹ in 2040-2070”.

Specific effects of climate change on US agriculture will be reviewed in Chapter XX.

2.3 Rising CO₂ and crop water use efficiency

Deryng et al. (2016) surveyed evidence on crop water productivity (CWP), i.e. yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them and once it was taken into account all regions showed a net CWP gain. Deryng et al (2016) also reported that negative impacts of warming on wheat and soybean yields from what?? were fully offset by CWP gains, and mitigated by up to 90% for rice and 60% for maize.

I don't think the figure is needed or particularly useful?

Figure 2.2 shows their Deryng et al.'s results. The gray bars report yield changes under warming alone and the green bars show the effects of warming after accounting for the CO₂ fertilization effect.



Figure 2.2: mean yield changes under RCP8.5 as of 2080 without CO₂ fertilization (gray) and with CO₂ fertilization (green). Data from Deryng et al. (2016).

Similar to this, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

2.5 Concealment of CO₂ fertilization benefits in IPCC Reports

If CO₂ emissions were discovered to be causing global crop declines and regional browning we would almost certainly have seen it discussed prominently in IPCC reports, and indeed it likely would have been the subject of its own chapter in an Assessment Report if not an IPCC Special Report on its own. By contrast the IPCC has been almost silent on the topic of global greening.

The topic is briefly acknowledged in a few places in the body of the IPCC 6th Assessment Report but is omitted in all Summary documents. Based on word searches here is what the most recent IPCC Summary documents (AR6) had to say about it:

Working Group I Summary for Policymakers: No mention.

~~Working Group I Technical Summary: No mention of greening. CO₂ fertilization mentioned twice: as a contributor via plant growth to the land carbon sink and as a contributor to the increased amplitude of the seasonal CO₂ cycle.~~

~~Working Group II Summary for Policymakers: No mention of greening except the observation that adding forest cover to cities can locally reduce temperatures. No mention of CO₂ fertilization.~~

~~Working Group II Technical Summary: No mention.~~

~~AR6 Synthesis Report: No mention.~~

~~AR6 Summary of Synthesis Report: (called the “Longer Report”): No mention.~~

The topic is briefly acknowledged in a few places in the body of the IPCC 6th Assessment Report but is omitted in all Summary documents.

Section 2.3.4.3.3 of the AR6 Working Group I report is titled “global greening and browning.” It points out that the IPCC Special Report on Climate Change and Land had concluded with high confidence that greening had increased globally over the past 2-3 decades. It then discusses the various estimate of greening trends, notes that there are variations in the estimates among data sets and then says that while they have high confidence greening has occurred, they have low confidence in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports. ~~But as noted, despite the volume of supporting evidence, news about global greening, improved plant water use efficiency and gains in crop production is omitted from the Summaries for Policymakers.~~

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6 Models versus Observations in the Recent Past

6.1 Introduction

Climate models are the primary tool used to project future climate changes in response to increasing atmospheric levels of anthropogenic greenhouse gases. They provide the theoretical evidence underpinning energy policy changes, such as efforts to reduce carbon dioxide emissions. In order to determine the value of climate models for this purpose, it is reasonable to ask how well they have reproduced climate variations over the recent past, say the last half-century.

Of great concern is the fact that, after several decades of the climate modeling enterprise involving approximately three dozen models operated by research centers around the world, the range of future warming they produce in response to a hypothetical doubling of atmospheric CO₂ extends over a factor of three. This range of disagreement among models has not changed for decades.

Problems with climate models are not just in their disagreement over the future, but also in their ability to replicate the recent past. Here we review some of the most important metrics of climate model accuracy: ability to reproduce historical surface, tropospheric and stratospheric temperature trends, ability to reproduce the vertical warming profile and ability to reproduce other climate features such as snowfall and humidity. In all cases a persistent finding is that models on average err on the side of too much warming in response to observed historical forcings.

6.2 Surface warming

A straightforward test of climate model validity is its ability to reproduce historical warming in response to known past changes in climate drivers such as greenhouse gases. Figure 6.1 is reproduced from Scaffeta (2023), a peer-reviewed 2023 study which groups the latest-generation (CMIP6) climate models into low ECS (1.5 to 3.0 degrees C), medium ECS (3.0 to 4.5 degrees C) and high ECS (4.5 to 6.0 degrees C), and compares their post-1980 global average temperature simulation ranges to those of three surface temperature records and one satellite-based lower troposphere temperature data product.

Columns correspond to model groups showing low-ECS to high-ECS. Rows correspond to widely-used observed temperature records, the first three showing surface averages and the fourth showing the lower troposphere average. In each panel the yellow area denotes the mean and range ($\pm$ one standard deviation) of climate model simulations for that group. The thick black line shows the observed annual average temperature in the indicated source.

Examination of the leftmost column shows that the low-ECS models track the post-1980 historical warming record reasonably well, but the middle and right columns show that the medium- and high-ECS models conspicuously over-predict the warming.

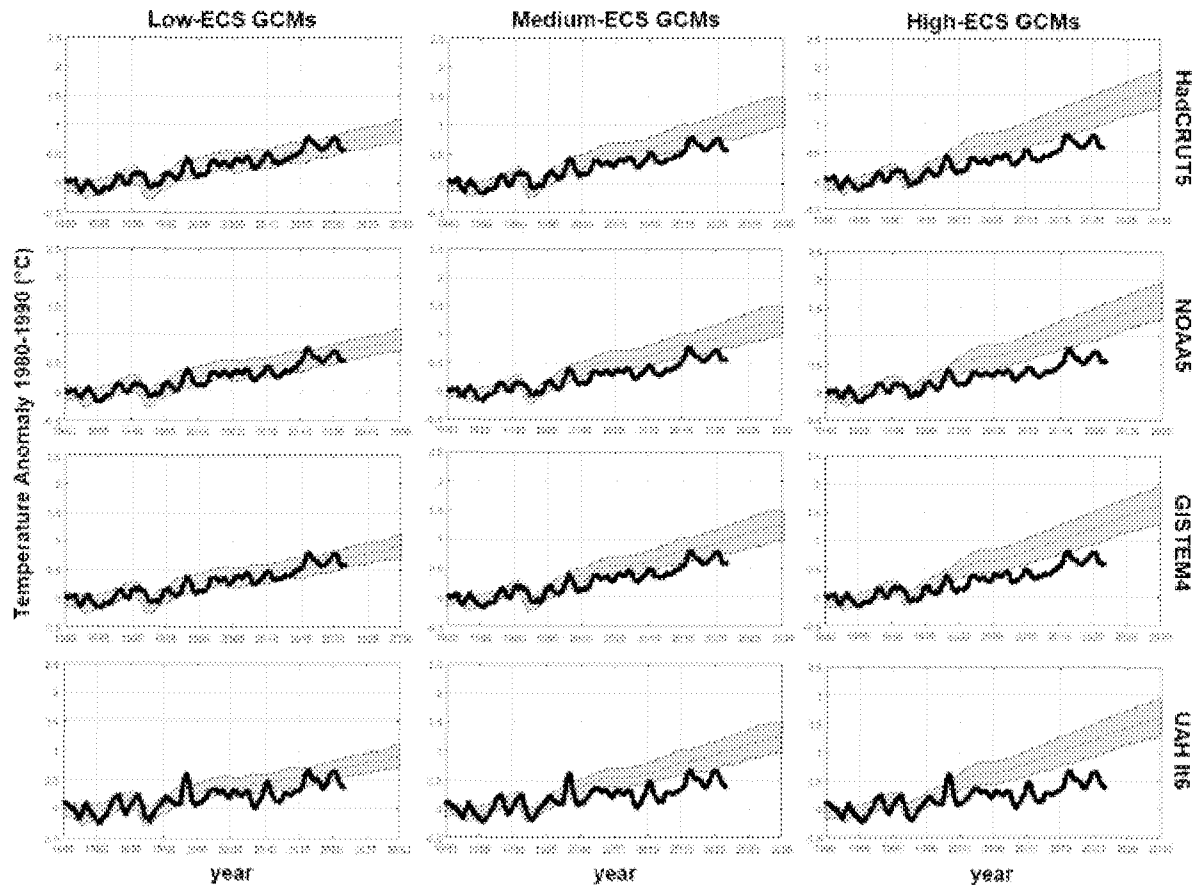


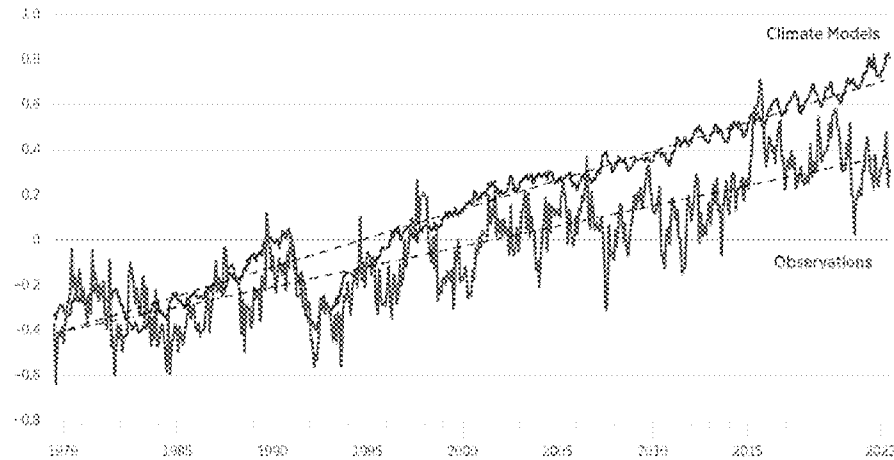
Figure 6.1: model-observational comparisons for Earth's surface warming. Source: Scafetta N. Climate Dynamics 2023 Fig.2. Rows: temperature data products as indicated. Columns: Low- to High-ECS models. Observations: black line. Model simulations: yellow band.

Spencer (2024) has also provided a useful summary of the Model-Observation mismatch by focusing on average surface temperature data products versus the average climate model warming, summarized in Figure 6.2.

CHART 1

Global Average Surface-Air Temperature Variations, 1979~2022

DEPARTURE FROM 1951-2020 AVERAGE, IN DEGREES CELSIUS



NOTE: Figures have been adjusted to align trends starting in 1979.

SOURCES: Authors' calculations based on data from five different observation-based datasets and 35 climate models taking part in the sixth IPCC Climate Model Intercomparison Project, and KNMI Climate Explorer, "Starting Point," <https://climate.knmi.nl/Start.asp> (accessed January 10, 2024).

Figure 6.2: Models versus observations at the surface. Source: Spencer (2024)

6.3 Tropospheric warming

It has long been known that climate models on average overstate warming in the troposphere over the tropics. Since this region generates the bulk of atmospheric warming in a GCM it is important to get the trends right. The discrepancy was flagged as a serious inconsistency in the first US Climate Change Science Program report (Karl et al. 2006) and has been mentioned in every IPCC report since, but it has gotten worse over time not better, and the bias is now global. McKittrick and Christy (2020) compare tropospheric warming rates in CMIP6 climate models to observations from satellites, weather balloons and reanalysis systems (Figure 6.3). Every single model overpredicts the observed warming trend in both Lower- and Mid-Troposphere layers, both globally and in the tropics (Figure 6.4).

In most individual cases the bias is statistically significant and on average it is highly significant. McKittrick and Christy (2020) also show that the bias is larger in high-ECS models, but even the models with lower average ECS predict too much warming. If a group of models were to appear that had a realistic representation of global tropospheric warming, it would likely have to have a lower ECS than even the low-ECS members of the CMIP6 ensemble

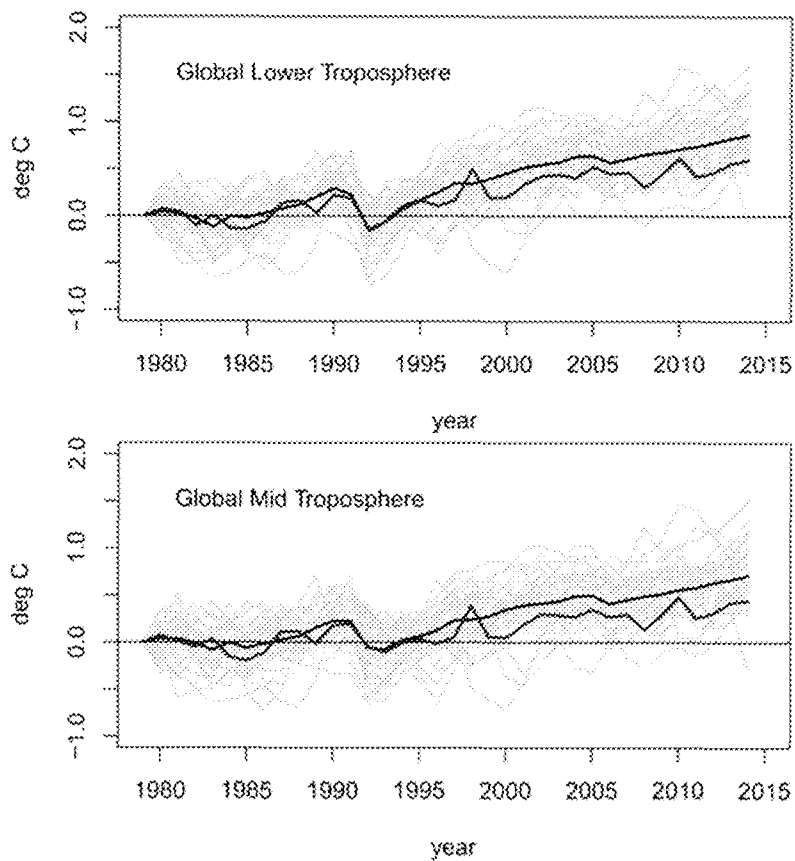


Figure 6.3: Models versus observations in the global troposphere. Source: McKittrick and Christy (2020). Gray lines: model runs. Black: average model run. Blue: average of satellite, radiosonde and reanalysis observations.

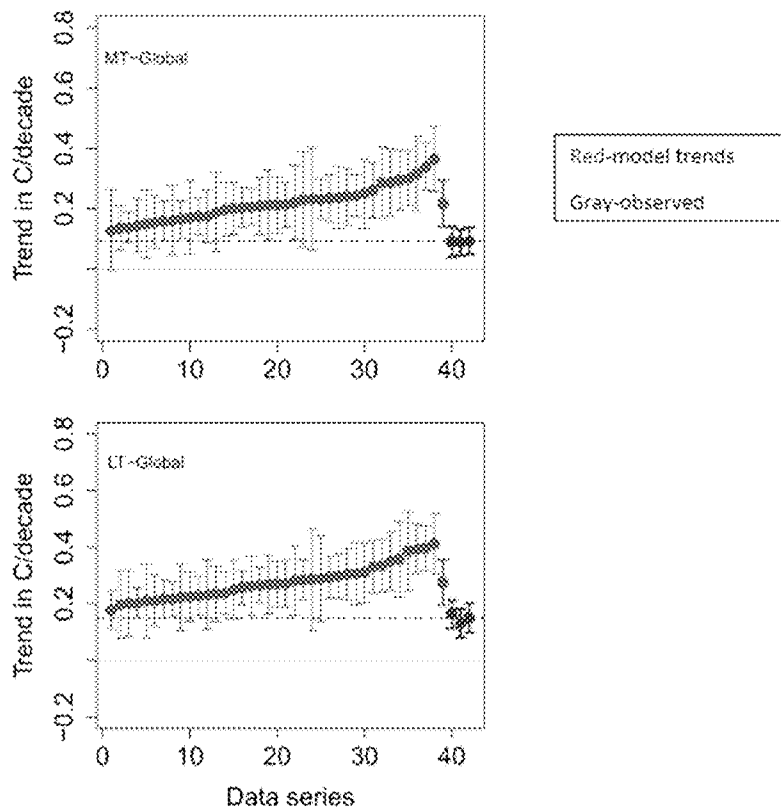


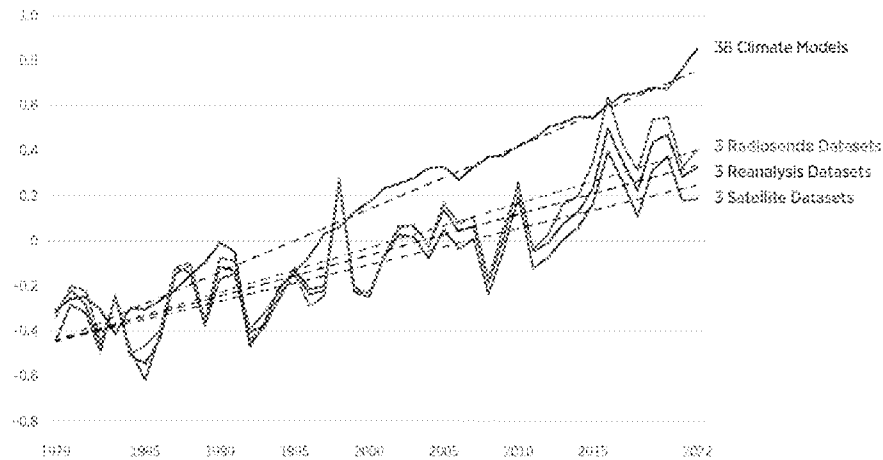
Figure 6.4: Modeled versus observed warming trends in the global troposphere. Adapted from McKittrick and Christy (2020). Red dots: model warming trend in $^{\circ}\text{C}/\text{decade}$ with 95% confidence interval bars. Gray dots: observed warming trends in 3 data products (satellite, radiosondes and reanalysis) and 95% confidence interval bars.

Spencer (2024) shows the mismatch is also present in the lower troposphere:

CHART 3

Global Lower Atmospheric Temperature Variations, 1979~2022

DEPARTURE FROM 1991-2020 AVERAGE, IN DEGREES CELSIUS



NOTE: Figures have been adjusted to align trends starting in 1979.

SOURCES:

- Author's calculations based on data from Ross McKittrick and John Christy, "Persistent Warming Bias in CMIP6 Tropospheric Layers," *Earth and Space Science*, Vol. 7, No. 11 (May 14, 2020), <https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2019JG006128> (accessed January 10, 2023).
- Author's calculations based on data from American Meteorological Society, *State of the Climate in 2022*, <https://www.wamweather.gov/index.cfm/analysis/outlook/bulletin-of-the-american-meteorological-society-bams/state-of-the-climate/> (accessed January 9, 2023).

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Figure 6.5: Comparison of average trends in lower troposphere, 1979-2022. Source: Spencer (2024).

As mentioned the IPCC has long acknowledged the model-observational mismatch. The AR6 pp. 443-444 confirms model-observational mismatch in the troposphere the tropics (it does not address the global comparison):

Several studies since AR5 have continued to demonstrate an inconsistency between simulated and observed temperature trends in the tropical troposphere, with models simulating more warming than observations (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; McKittrick and Christy, 2018; Po-Chedley et al., 2021)... Over the 1979–2014 period, models are more consistent with observations in the lower troposphere, and least consistent in the upper troposphere around 200 hPa, where biases exceed 0.1°C per decade. Several studies using CMIP6 models suggest that differences in climate sensitivity may be an important factor contributing to the discrepancy between the simulated and observed tropospheric temperature trends (McKittrick and Christy, 2020; Po-Chedley et al., 2021), though it is difficult to deconvolve the influence of climate sensitivity, changes in aerosol forcing and internal variability in contributing to tropospheric warming biases (Po-Chedley et al., 2021). Another study found that the absence of a hypothesized negative tropical cloud feedback could explain half of the upper troposphere warming bias in one model (Mauritsen and Stevens, 2015).

... In summary, studies continue to find that CMIP5 and CMIP6 model simulations warm more than observations in the tropical mid- and upper-troposphere over the 1979–2014 period (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; Suárez-Gutiérrez et al., 2017; McKittrick and Christy, 2018), and that overestimated surface warming is partially responsible (Mitchell et al., 2013; Po-Chedley et al., 2021). Hence, we assess with *medium confidence* that CMIP5

and CMIP6 models continue to overestimate observed warming in the upper tropical troposphere over the 1979–2014 period by at least 0.1°C per decade,

It is worth noting that despite the enormous accumulation of evidence of excess model warming the IPCC only assigns *medium confidence* to the existence of a warming bias. In other contexts they declare *high confidence* in phenomena established with much less evidence.

6.4 Vertical profile mismatch and excess amplification

An important element of the model-observational discrepancy is the excess amplification with altitude found in climate models. A comparison was shown in the IPCC AR5 Chapter 10, although only in the online supplement. The diagram, reproduced below as Figure 6.6, compares temperature trends by altitude between models and observations, divided up into latitude bands.

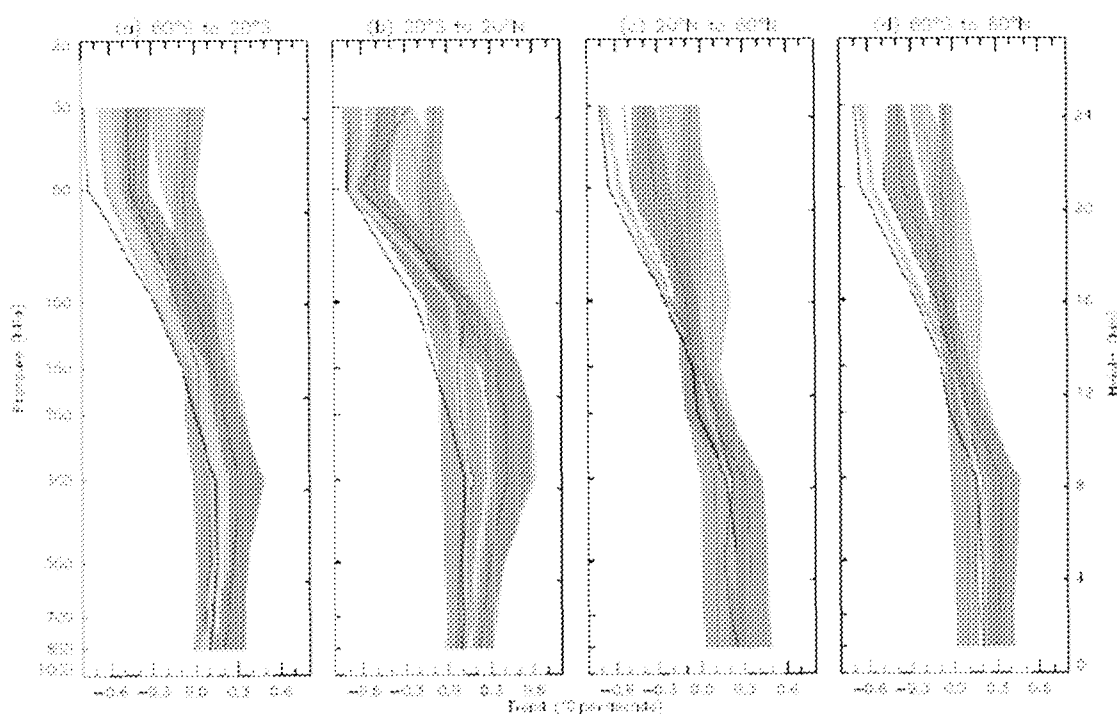


Figure 10.SM.1 | Observed and simulated mean temperature trends from 1979 to 2010 for CMIP5 simulations containing both anthropogenic and natural forcings (left), natural forcings only (blue) and greenhouse gas forcing only (green) where the 10th to 90th percentile ranges of the ensembles are shown. Three radiance observations are shown: black (left line: Hadley Centre Atmospheric Temperature data set 2 (HadAT2)), thin black line: Radiance Observation Collection using Radiance (RADOCOL) 1.5, dark gray (wide): Radiance Observation Composite (RADOCOL) 1.5 ensemble and light gray: RCM-1.5 ensemble (Adapted from Li et al. (2018) but for the more recent period from 1979 to 2010.)

10542-6

Figure 6.6: Vertical warming pattern by latitude band. Source: IPCC AR5 Figure 10.SM.1

The Figure is not referenced in the main report nor in any summary. What it shows, although it is not apparent at first glance, is that the 1979-2010 warming in the lower troposphere is so minimal it is consistent with models having no GHG forcing in them at all, and is inconsistent with the model runs that do have GHG forcing. Here is the main global band (60S to 60N) expanded with the observed trends highlighted in yellow:

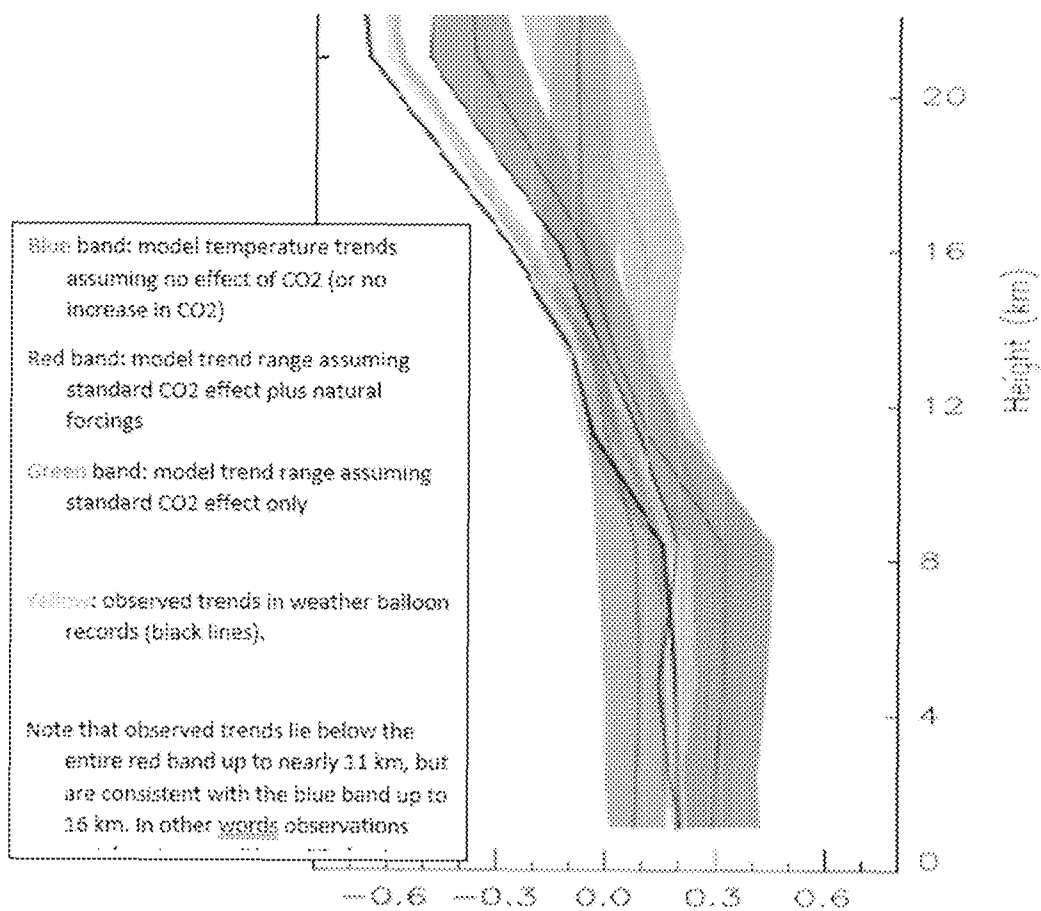


Figure 6.7: Adapted from IPCC AR5 Figure 10.SM.1

The next version of the Figure draws further detail out of the tropics band:

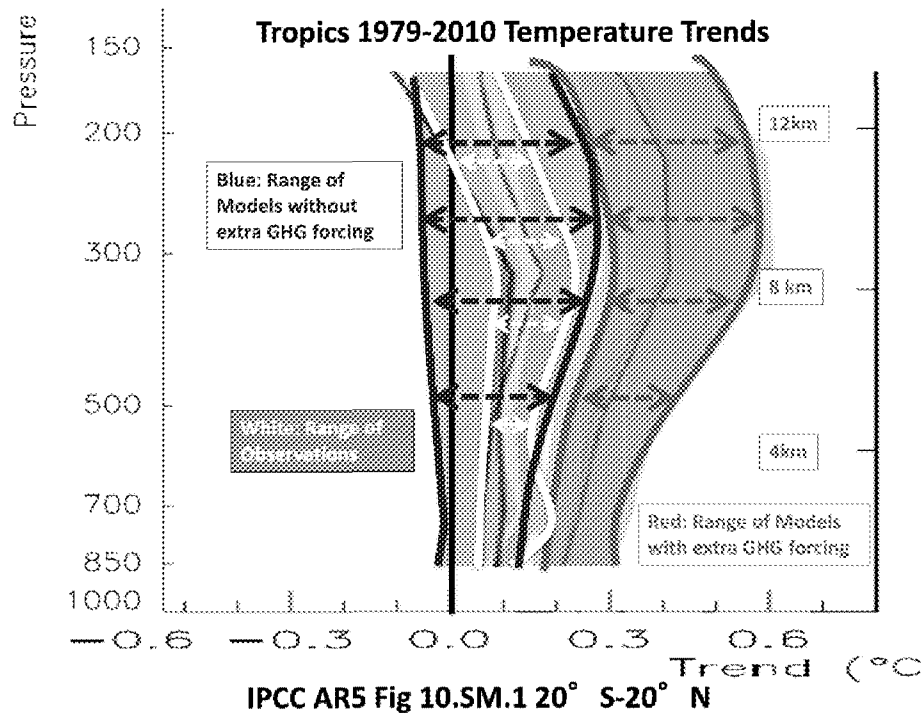


Figure 6.8: Adapted from IPCC AR5 Figure 10.SM.1.

In the tropics, where the models say the warming should be strongest, the observations (shown here in white) lie within the “No CO₂” band and entirely outside the “with CO₂” red envelope. This means that in the entire tropical atmospheric column from the surface to the stratosphere, *observed warming trends are so small they are consistent with the output of models that have no CO₂ warming effect in them, and they are inconsistent with the entire envelope of warming trends generated by models forced with increased CO₂.*

A similar comparison is shown in Christy and McNider (2017), an updated version of which (covering 1979-2024) is reproduced as Figure 6.9. Modeled temperature trends exceed balloon observations from the surface through the top of the troposphere, with observed trends below the entire model range at most pressure levels. Also shown in Figure 6.9 is the TTT layer average from three satellite data products (NOAA, UAH and RSS) compared to the same layer average from climate models for 1979-2024. Again the observed trends lie below the entire model range.

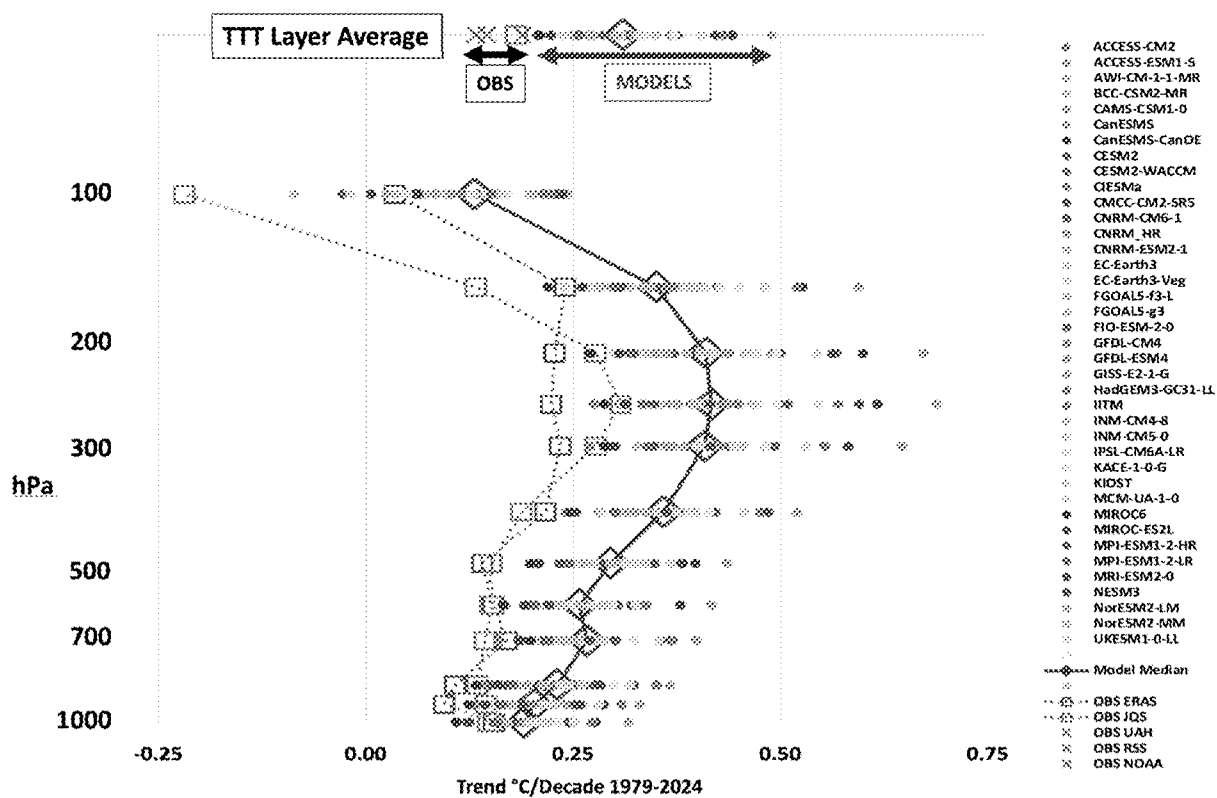


Figure 6.9: Modeled versus observed warming, tropical troposphere. Source: Christy and McNider (2017).

Some defenders of the models have argued that even if there is very little observed warming aloft in the tropics, a “hotspot” still exists in the sense that the warming aloft is greater than at the surface. But there is good evidence that models also exaggerate the amplification rate. Klotzbach et al. (2009), which was not discussed in the AR6, showed that models project greater amplification with altitude than is observed. That paper gave rise to an online debate over whether the amplification rates were being correctly calculated, and whether the discrepancy between models and observations was statistically significant. The topic involves very advanced statistical theory and was dealt with by two experts in time series analysis (Vogelsang and Nawaz 2016) who found that Klotzbach’s conclusions were valid, and that observed amplification is significantly smaller than the model-projected rates. The IPCC AR6 made no mention of this work either.

6.5 Stratospheric cooling

An important element of the expected general “fingerprint” of anthropogenic climate change is simultaneous warming of the troposphere and cooling of the stratosphere. The IPCC AR6 acknowledged that cooling had been observed but only up to 2000. Thereafter the stratosphere has exhibited some warming, contrary to model projections.

The AR6 WG1 Ch 2 pp. 327-9 states (emphasis added):

“Temperatures averaged through the full lower stratosphere (roughly 10–25 km) have decreased over 1980–2019 in all data products, with the bulk of the decrease prior to 2000. The decrease holds even if the influence of the El Chichon (1982) and Pinatubo (1991) volcanic eruptions on the trend, found by Steiner et al. (2020a) to have increased the 1979–2018 cooling trend by 0.06°C per decade, is removed. **Most datasets show no significant or only marginally significant trends over 2000–2019, and the results of Philipona et al. (2018) show weak increases over 2000–2015** in the very lowermost stratosphere sampled by radiosondes....

It is virtually certain that the lower stratosphere has cooled since the mid-20th century. However, most datasets show that **lower stratospheric temperatures have stabilized since the mid-1990s with no significant change over the last 20 years**. It is likely that middle and upper stratospheric temperatures have decreased since 1980, but there is low confidence in the magnitude.

The cited source, Philipona et al. (2018), in an article entitled “Radiosondes Show That After Decades of Cooling, the Lower Stratosphere Is Now Warming”, stated:

“In response to continued greenhouse gas increases and stratospheric ozone depletion, climate models project continued tropospheric warming and stratospheric cooling over the coming decades. Global average satellite observations of lower stratospheric temperatures exhibit no significant trends since the turn of the century. In contrast, an analysis of vertically resolved radiosonde measurements from 60 stations shows an increase of lower stratospheric temperature since the turn of the century at altitudes between 15 and 30 km and over most continents. Trend estimates are somewhat sensitive to homogeneity assessment choices, but all investigated radiosonde data sets suggest a change from late twentieth century cooling to early 21st century warming in the lower stratosphere.”

6.6 Water vapour trends mismatch

Much of the warming in climate models derives not from GHG increases themselves but from water vapour feedbacks: extra warming induced by the projected accumulation of water vapour in the atmosphere after it warms due to CO₂. But new evidence (Simpson et al. 2024) shows that models have over-projected increases in humidity.

“Water vapor in the atmosphere is expected to rise with warming because a warmer atmosphere can hold more moisture. However, over the last four decades, near-surface water vapor has not increased over arid and semi-arid regions. This is contrary to all climate model simulations in which it rises at a rate close to theoretical expectations, even over dry regions. This may indicate a major model misrepresentation of hydroclimate-related processes; models increase water vapor to satisfy the increased atmospheric demand, while this has not happened in reality.”
(Simpson et al. 2024)

While the models and observations matched over the 1988 to 2006 interval they diverge after that, directly contradicting model projections.

6.7 Snow cover mismatch

According to the Rutgers University Snow Lab (undated) the Northern Hemisphere winter snow cover shows an increasing trend over time.

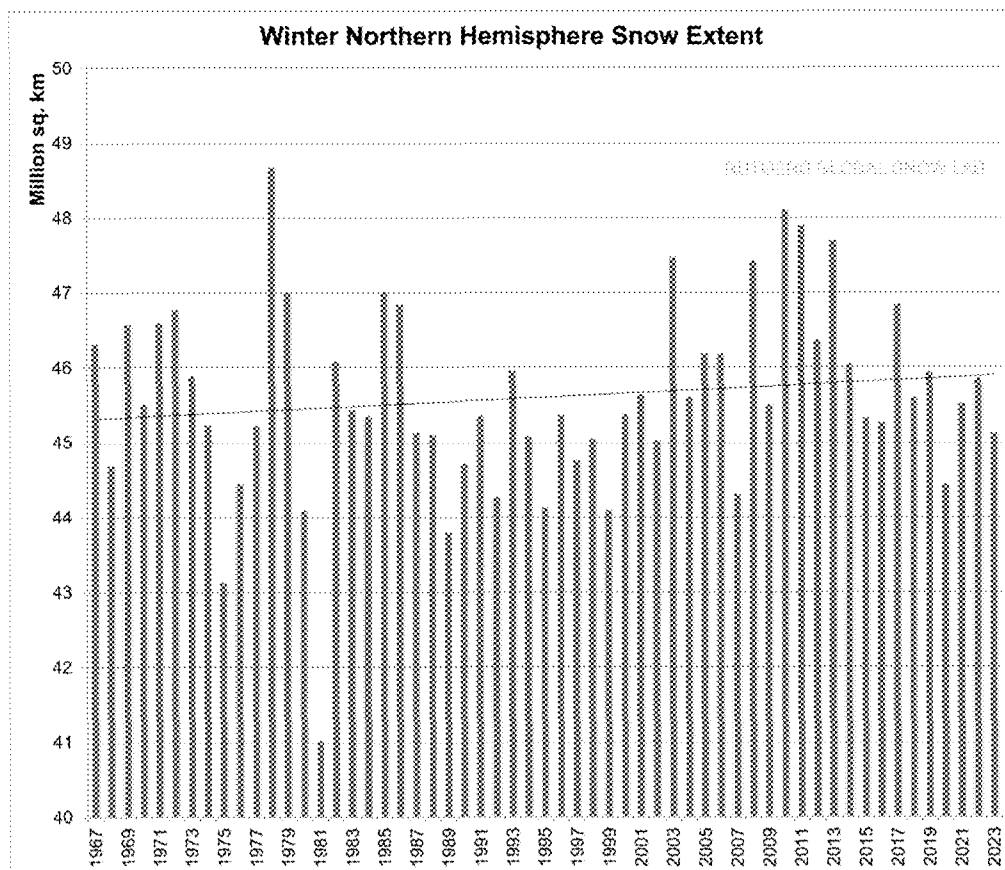


Figure 6.10: Northern Hemisphere Winter Snow extent. Source: https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1 (February 24, 2024)

Models project declining Northern Hemisphere snow cover due to climate warming. But observations do not support this, as explained by Connolly et al. (2019).

Observed changes in Northern Hemisphere snow cover from satellite records were compared to those predicted by all available Coupled Model Intercomparison Project Phase 5 (“CMIP5”) climate models over the duration of the satellite’s records, i.e., 1967–2018. A total of 196 climate model runs were analyzed (taken from 24 climate models). Separate analyses were conducted for the annual averages and for each of the seasons (winter, spring, summer, and autumn/fall). A longer record (1922–2018) for the spring season which combines ground-based measurements with satellite measurements was also compared to the model outputs. **The climate models were found to poorly explain the observed trends. While the models suggest snow cover should have steadily decreased for all four seasons, only spring and summer exhibited a long-term decrease, and the pattern of the observed decreases for these seasons was quite different from the modelled predictions.** Moreover, the observed trends for autumn and winter suggest a long-term increase, although these trends were not statistically significant. Connolly et al. (2019), emphasis added.

6.8 US Corn Belt

One of the largest discrepancies between models and observations can be found when we test them in a region of particular importance to global food production: the U.S. Corn Belt. Fig. 6.11 shows the warming trends for summertime (June, July, August) for the U.S. 12-state Corn Belt (IN, IA, NE, ND, SD, MO, MN, WI, MI, OH, KS, NE) during 1973-2022. All 36 climate models (red) produced too much warming compared to observations (blue) during 1973 to 2022.

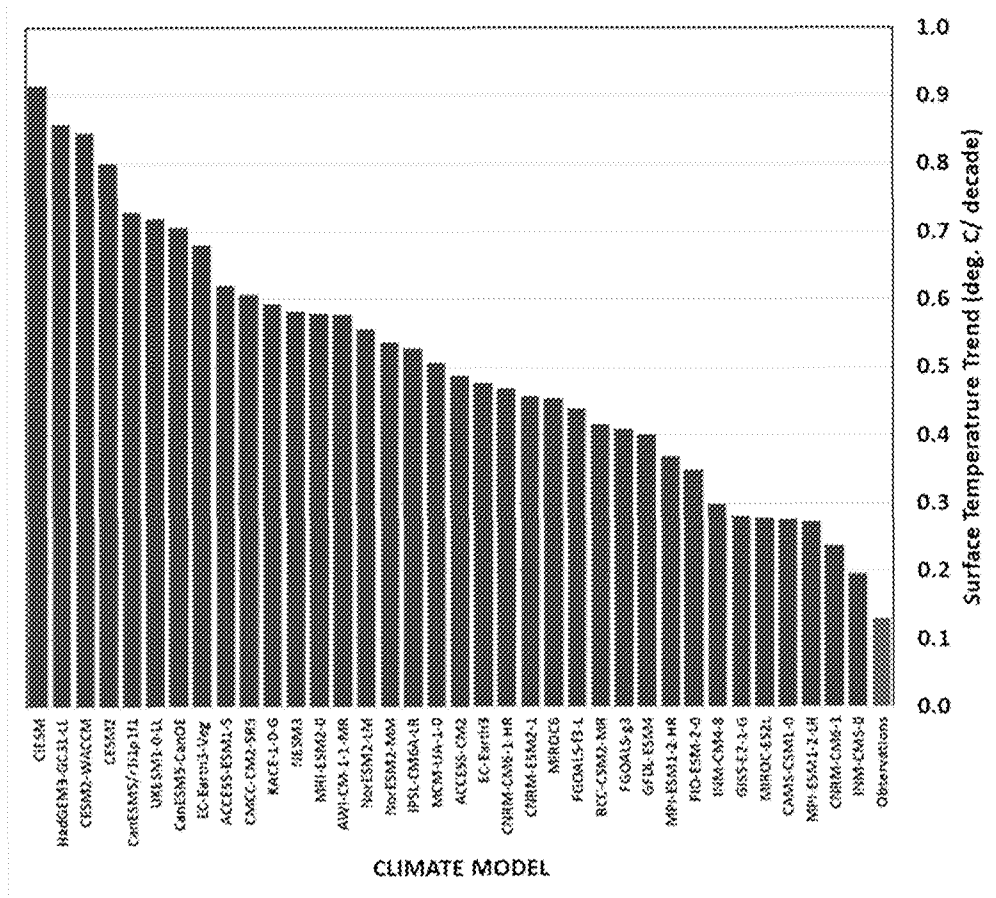


Figure 6.11: Modeled versus observed warming trends in the US corn belt.

As discussed in Chapter 10, the anticipated negative effects of increasing temperatures on U.S. corn yields have not materialized, which is in contrast to widely publicized studies proclaiming that theoretical future impacts are already being experienced (e.g. Seager et al., 2017).

Summarizing:

- Climate models show warming biases in many aspects of their reproduction of the past few decades.
- They produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower-and mid-troposphere and too much amplification of warming aloft
- They also produce too much stratospheric cooling, too much water vapor increase, too much snow loss, and too much warming in the corn belt.
- The IPCC has acknowledged some of these issues, buried the amplification problem and ignored others.

- The warm bias discussed here is consistent with independent evidence of model bias presented in Chapters 5 (measuring climate sensitivity) and 7 (optimal fingerprinting). Given the persistent warm bias in so many key aspects of climate model performance, users are justified in assuming that projections of future warming are also very likely to be biased too warm.

9 Changes in Sea level

Arguably the most important climate impact driver that is unambiguously associated with increasing temperatures is global sea level rise. Global warming increases sea level rise through thermal expansion of the volume of sea water and melting of glaciers and ice sheets. Another factor that influences sea level variations is land water storage. Regional sea level change is influenced by large-scale ocean circulation patterns, and geologic processes and deformation from the redistribution of ice and water. Local sea level rise is further influenced by vertical land motion from geologic processes, ground water withdrawal, and fossil fuel extraction.

The IPCC AR6 estimates that global mean sea level increased by 7.9 (5.9–9.8) inches between 1901 and 2018. The rate of sea level rise has accelerated in recent decades. At the ocean basin scale, sea levels have risen fastest in the Western Pacific and slowest in the Eastern Pacific over the period 1993–2018.¹ The rate of global sea level rise is estimated to be 0.12 inches/year (for reference: 0.12 in is the height of two stacked pennies).²

The observing systems for global sea level rise have advanced significantly in the satellite era, particularly with the advent of satellite altimeters since 1993. Local tide gauges have provided useful data for the past century, and even longer for a few locations. Following the end of the Little Ice Age in the mid-nineteenth century, tide gauges show that the global mean sea level began rising during the period 1820–1860.

9.1 U.S. coastal sea level rise

Observed and predicted rates of mean global sea level rise may have little relevance for specific locations³. In Canada and Alaska (and also northern Washington), sea level is actually decreasing, owing to uplift from glacial rebound. Most of the Pacific coast has rates of sea level rise of 0 to 0.12 inches/year. The largest rates of sea level rise are on the Gulf coast (Louisiana and Texas) and in the mid-Atlantic states (Chesapeake Bay region).

Measurements of relative sea level rise from tide gauges conflate the rise in the volume of seawater with local vertical land motion. Hence in examining local sea level changes, it is important to also consider the local vertical land motion. Absolute local sea level rise is the sum of relative sea level rise and the local vertical land motion.

A wide range of processes can cause vertical land motion along the coasts, having amplitudes comparable to the sea level signals expected from land-ice melting or ocean thermal expansion. Vertical land motion on the coasts can locally exacerbate (subsidence/sinking) or mitigate (uplift) the risk of sea level rise. Local changes in sea level vary considerably from place to place and can

¹ B. Fox-Kemper et al., “Ocean, Cryosphere and Sea Level Change,” in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, CH: Intergovernmental Panel on Climate Change, 2021), 1211-1362.

² “Rising Waters: How NASA Is Monitoring Sea Level Rise,” NASA (NASA), accessed May 19, 2022, <https://www.nasa.gov/specials/sea-level-rise-2020/>.

³ <https://tidesandcurrents.noaa.gov/sltrends/>

deviate substantially from the rate of global mean sea level change.⁴ Human activities triggering subsidence are soil drainage (e.g. for urban development purposes) or subsurface mining of resources such as groundwater, oil or gas. The magnitude of relative sea level rise caused by human activities is often considerable. Local vertical land motion of relevance to local sea level change is best measured using a Global Positioning System (GPS) station located in the location as the tide gauge.

Table 8.1 shows absolute sea-level rise (ASLR) for selected locations, determined from the sum of uncorrected sea-level rise as estimated from tide gauge time series (RSLR)⁵ and the vertical land motion (VLM)^{6, 7,8} measurements. The absolute sea level rise for each of these locations is significantly smaller than the measured relative sea level rise owing to local sinking of the land. More than half of the measured relative sea level rise is attributed to land sinking for these locations: San Francisco, Galveston, Grand Isle. For reference, the global average rate of absolute sea level rise is estimated to be 0.12 inches/year.

Table 8.1 Absolute sea level rise (inches/year) (RSLR plus VLM)

Location	RSLR	VLM	ASLR
San Francisco, CA	+0.08	-0.06	+0.02
Galveston, TX	+0.26	-0.19	+0.07
Grand Isle, LA	+0.36	-0.28	+0.08
St Petersburg, FL	+0.12	-0.02	+0.10
New York City, NY	+0.11	-0.05	+0.06

San Francisco Bay

Over the past 100 years, relative sea level in the San Francisco Bay area has risen by 7.8 inches, at an average rate of 0.08 inches/year (Figure 8.1). As shown in Table 6.1, San Francisco's vertical land motion is -0.06 inches/year (sinking), producing a recent rate of absolute sea level rise of +0.02 inches/year. Portions of Treasure Island, San Francisco International Airport, and Foster City are sinking as fast as 0.4 inches/year.⁹ Landfill zones are sinking due to soil compaction, at a rate as much as one-half inch per year, threatening coastal infrastructure including the San Francisco International Airport. The problems in the San Francisco Bay area have been caused primarily by sinking in landfill regions that were formerly wetlands, not by the slow creep of global sea level rise.

⁴ Wöppelmann, G., and M. Marcos (2016), Vertical land motion as a key to understanding sea level change and variability, *Rev. Geophys.*, 54, 64–92.

⁵ NOAA Tides & Currents, Relative Sea Level Trends - <https://tidesandcurrents.noaa.gov/sltrends/>

⁶ NAS (2012) *Sea-Level Rise for the Coasts of California, Oregon and Washington: Past, Present, and Future*. Appendix A: Vertical Land Motion and Sea-Level Data Along the West Coast of the United States. National Academies Press, NAP.edu/10766.

⁷ Letetrel, C, M Karpytchev, MN Bouin et al (2015) Estimation of vertical land movement rates along the coasts of the Gulf of Mexico over the past decades. *Continental Shelf Research*, 111, 42-51.

⁸ Karegar, MA, TH Dixon, SE Engelhart (2016), Subsidence along the Atlantic Coast of North America: Insights from GPS and late Holocene relative sea level data, *Geophys. Res. Lett.*, 43, 3126–3133, doi:10.1002/2016GL068015.

⁹ Shirzaei, M, R Burgmann (2018) Global climate change and local land subsidence exacerbate inundation risk to the San Francisco Bay Area. *Science Advances*, 4, eaap9234

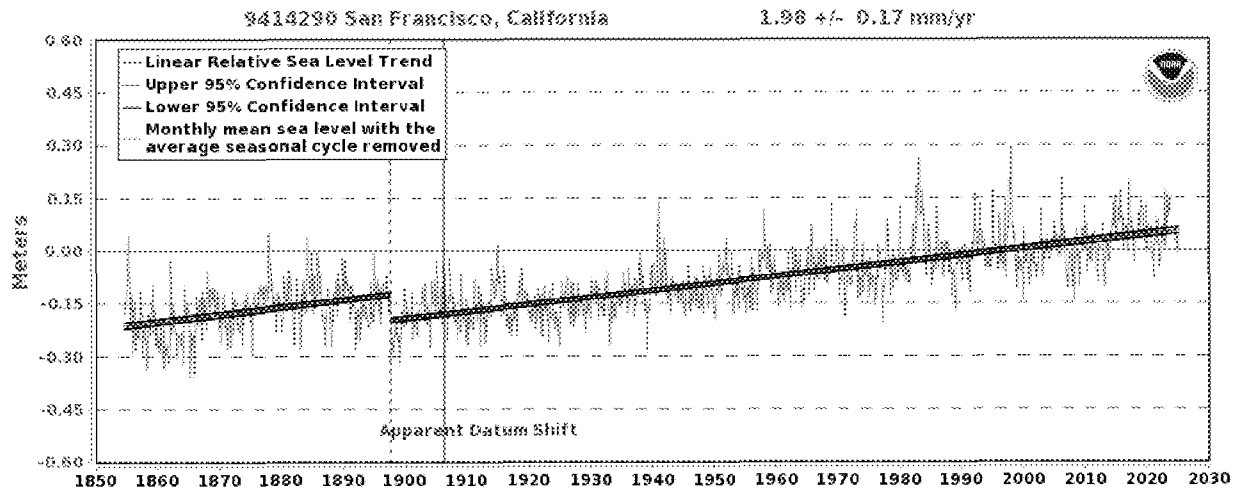


Figure 8.1. Tide gauge measurements at San Francisco, California, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=9414290 (downloaded 4/22/25).

Galveston - Houston

Long-term tide measurements at Galveston Pier 21 show sea level rise of 2.18 feet in the past century, or a rate of 0.26 inches/year (Figure 8.2). Vertical land motion (subsidence) at Galveston is estimated at -0.19 inches/year, yielding a value of absolute sea level rise of +0.07 inches/year (Table 8.1). The U.S. Geologic Survey found that most of the land-surface subsidence in the Houston-Galveston region has occurred as a direct result of groundwater withdrawals.¹⁰ This caused compaction of the aquifer sediments, mostly in the fine-grained silt and clay layers. By 1979, as much as 10 feet of subsidence had occurred in Houston.

Hurricanes are traditionally the major concern in the region. The 1900 hurricane that struck Galveston and killed between 6,000 and 12,000 people is still considered the United States' deadliest natural disaster.¹¹ Hurricane Ike (2008) decimated large portions of the Bolivar Peninsula literally removing significant portions of the land mass.¹² While only 17 people were killed in Texas, property damage exceeded \$50 billion.¹³ In 2017, Hurricane Harvey struck the region, bringing catastrophic rainfall-triggered flooding that inflicted over \$125 billion in damages.¹⁴

¹⁰ Kasmarek, M.C., and Ramage, J.K., 2017, Water-level altitudes 2017 and water-level changes in the Chicot, Evangeline, and Jasper aquifers and compaction 1973–2016 in the Chicot and Evangeline aquifers, Houston-Galveston region, Texas: U.S. Geological Survey Scientific Investigations Report 2017–5080, 32 p., <https://doi.org/10.3133/sir20175080>.

¹¹ Weems, John Edward, "Galveston Hurricane of 1900", Texas State Historical Association, (March 15, 2016) <https://www.tshaonline.org/handbook/entries/galveston-hurricane-of-1900>.

¹² "Galveston County, Texas, Faces Sea Level Rise and Storms", Union of Concerned Scientists, (June 23, 2017) <https://www.ucs.org/resources/galveston-county-texas-faces-sea-level-rise-and-storms>.

¹³ White, Audrey, "Galveston Still Healing 5 Years After Hurricane Ike", The Texas Tribune, (April 26, 2013) <https://www.texastribune.org/2013/04/26/galveston-still-healing-5-years-after-hurricane-ike/>.

¹⁴ NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2025). <https://www.ncei.noaa.gov/access/billions/>, DOI: 10.25921/stkw-7w73

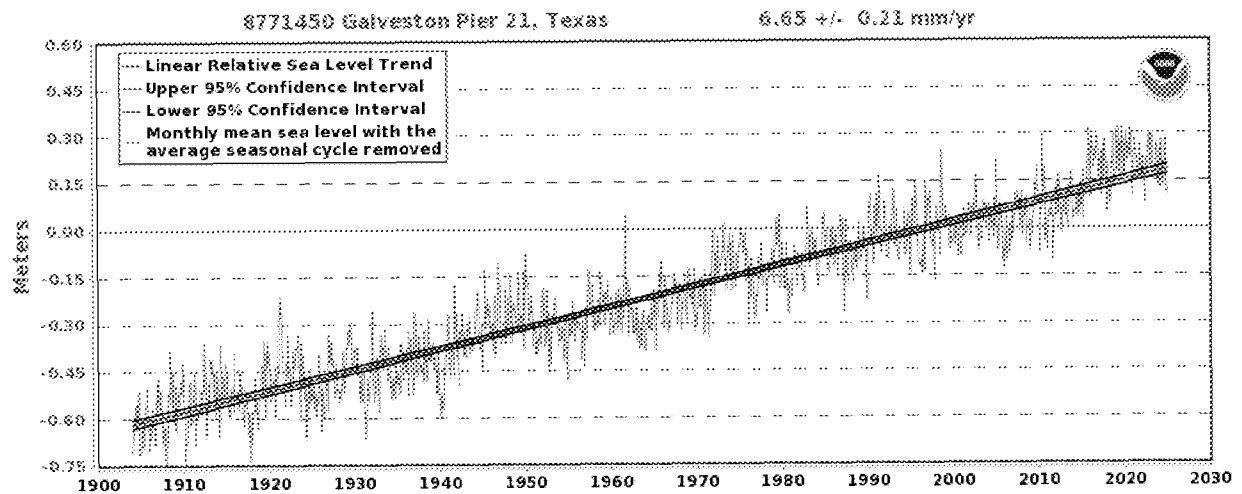


Figure 8.2. Tide gauge measurements Galveston Pier, TX, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8771450 (downloaded 4/22/2025).

New Orleans and the Mississippi delta

There are long-term tide gauge measurements at Grand Isle, Louisiana, respectively estimating that sea level has risen slightly more than 3 feet over the last 100 years and at an average rate of 0.36 inches/year (Figure 8.3). Vertical land motion (subsidence) is estimated -0.28 inches/year at Grand Isle. From Table 6.1, the absolute sea level rise is +0.08 inches/year at Grand Isle.

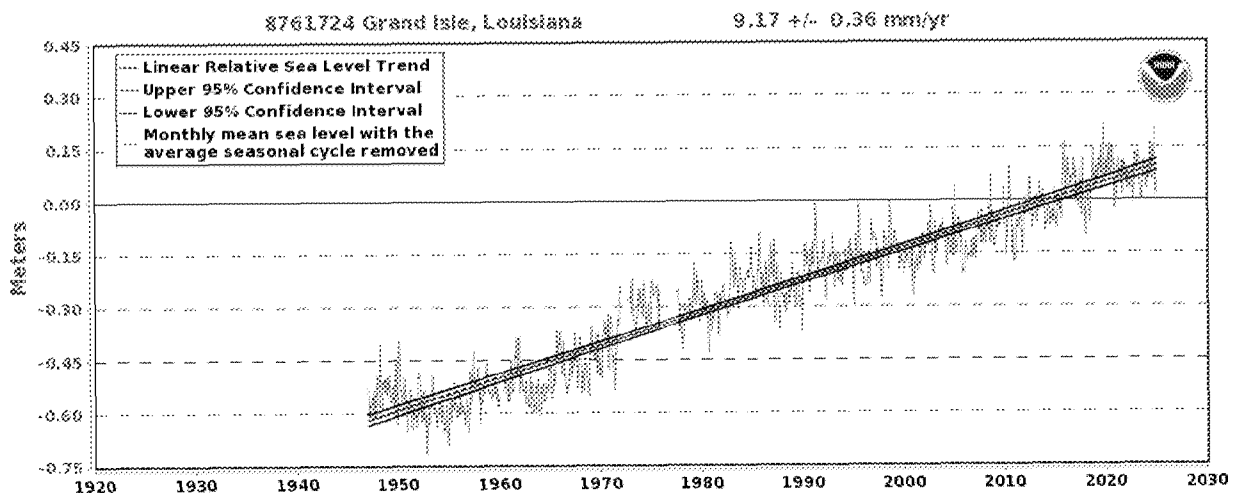


Figure 8.3. Tide gauge measurements at Grand Isle, LA, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8761724 (downloaded 4/22/25).

The issues of sea level rise and land loss in the Mississippi delta region are complex, with geological subsidence and the decline in sediment transported by the Mississippi river being the dominant drivers. Due to the construction of dams in the basin since the 1950s, the suspended

sediment load of the Mississippi River has decreased by ~50%.¹⁵ A new subsidence map of coastal Louisiana finds the coastal region to be sinking at about one third of an inch per year.¹⁶ For a city whose elevation averages one to two feet below sea level, sea level rise from human caused warming is not the dominant driver for the problems that New Orleans is facing.

New York City

New York City is particularly vulnerable to the effects of sea level rise because it is built primarily on islands and has 520 miles of coastline. In New York City, relative sea level has risen over 11 inches over the past century, at an average rate of 0.11 inches/year (Figure 8.4). Vertical land motion in the New York City area is occurring at a rate of -0.05 inches/year (subsidence), corresponding to roughly 5 inches per century. From Table 6.1, the absolute rate of sea level rise at The Battery location is 0.06 inches/year, or about 55% of the measured relative sea level rise.

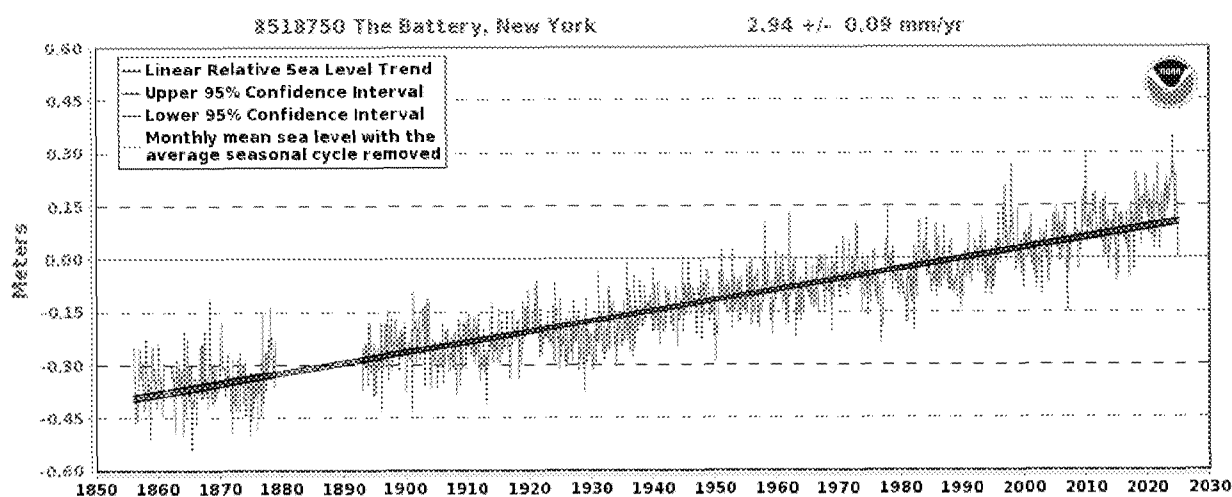


Figure 8.4. Tide gauge measurements at The Battery, New York, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750 (downloaded 4/22/25).

Following Hurricane Sandy, New York has developed a comprehensive plan: *City of New York: Building a Stronger, More Resilient New York*.¹⁷ A broad range of coastal protection measures are outlined that match the risks facing a given area: increase coastal edge elevations, minimize upland wave zones, infrastructure to protect against storm surge, improve coastal design and governance, restore estuaries wetlands, coastal nourishment, site elevation, and drainage systems.

¹⁵ Jillian M. Maloney et al., “Mississippi River Subaqueous Delta Is Entering a Stage of Retrogradation,” *Marine Geology* 400 (June 2018): 12–23, <https://doi.org/10.1016/j.margeo.2018.03.001>.

¹⁶ Jaap H. Nienhuis et al., “A New Subsidence Map for Coastal Louisiana,” *GSA Today* 27, no. 6 (June 2017): 28–29, <https://doi.org/10.1130/GSATG337GW.1>.

¹⁷ City of New York, *A Stronger, More Resilient New York* (New York: City of New York, June 2013), http://s-media.nyc.gov/agencies/sirr/SIRR_singles_Hi_res.pdf.

9.2 Sea level rise projections

The concern over sea level rise is not about the 8 inches or so that global mean sea level has risen since 1900. Rather, the concern is about projections of 21st century sea level rise based on climate model-based projections of human-caused global warming.

The IPCC AR6 finds that there is *high agreement* across published global mean sea level projections for 2050 and there is little sensitivity to emissions scenarios. Considering only projections incorporating ice-sheet processes in whose quantification there is at least *medium confidence*, the global sea level projections for 2050, across all emissions scenarios, fall between 3.94 and 15.75 inches (5th–95th percentile *very likely* range) relative to the 1995–2014 baseline period.¹⁸

Conversely, there is *low agreement* across published global mean sea level projections for 2100, particularly for higher emissions scenarios. Considering only projections representing processes in whose quantification there is at least *medium confidence*, the AR6 global mean sea level projections for 2100 lie between 7.87 and 39.37 inches (5th–95th percentile *very likely* range) under the medium emissions scenario SSP2–4.5.¹⁹ There is deep uncertainty surrounding projections of sea level rise to 2100, particularly for the higher emissions scenarios.

In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995–2014), almost half of the sea level rise has already occurred by 2025. From the tide gauge measurements in Figures 8.1–8.4, there is no obvious acceleration in sea level rise beyond the historical average rate of sea level rise.

9.3 Summary

Since 1900, global sea level has risen by about 8". Sea level change along U.S. coasts is highly variable, associated with local variations in processes that contribute to sinking and also ocean circulation patterns. The highest levels of sea level rise along U.S. coasts are Galveston, New Orleans, and the Chesapeake Bay regions – each of these locations is associated with substantial local sinking that is unrelated to climate change.

Extreme projections of global sea level rise are associated with the implausible extreme emissions scenario and inclusion of poorly understood processes associated with hypothesized ice sheet instabilities. In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995–2014), almost half of the sea level rise has already occurred by 2025 and at a lower rate than predicted. From the tide gauge measurements in Figures 8.1–8.4, there is no obvious acceleration in sea level rise beyond the historical average rate of sea level rise.

¹⁸ B. Fox-Kemper et al., “Ocean, Cryosphere and Sea Level Change,” in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, CH: Intergovernmental Panel on Climate Change, 2021), 1211–1362.

¹⁹ B. Fox-Kemper et al., “Ocean, Cryosphere and Sea Level Change.”

10. Climate change and US agriculture

10.1 Econometric analyses

Econometric analyses of the effects of climate change on agriculture have sought to integrate information about long term crop yield changes in response to temperature and precipitation changes under assumptions about adaptive behavior by farmers. One method focuses on variations in agricultural land values. The rationale is that if climate change is a long-term net benefit for agriculture it should translate into higher market values for agricultural land, and vice versa. While individual crops might benefit from or be harmed by climate change, once the adaptive responses of farmers are taken into account the value of farmland represents an index of whether the changes are expected to be beneficial or not. Mendelsohn et al. (1994) examined the relationship between historical climatic variations on agricultural land values and concluded global warming would be slightly beneficial to American agriculture.

The Mendelsohn et al. method, called Ricardian analysis after David Ricardo, the 19th century British economist who pioneered the study of land values, attracted subsequent criticism from authors who argued it failed to account for differences in land values attributable to fixed locational characteristics like soil quality, and non-climatic changes including nearby urbanization. Deschênes and Greenstone (2007) looked at agricultural profits instead of land values and reached similar conclusions to Mendelsohn et al. (1994), namely that past climatic variations had relatively little effect on farm profitability and that warming would likely yield small overall benefits for the US agricultural sector. However a subsequent exchange with critics led them (Deschênes and Greenstone 2012) to revise their conclusions and project potentially large losses in US agriculture due to climate warming. Burke and Emerick (2016) looked at temperature variations over 1980 to 2000 and argued that farmers were not as able to adapt to temperature changes as the Ricardian method assumes and that climate change would have large negative impacts on corn and soy yields. Schlenker and Roberts (2009) similarly argued that yield gains to past warming would not carry over to the future and corn and soy yields would sharply decrease this century due to climate change.

Two recent studies have argued that pessimistic findings such as these are not robust. Ortiz-Bobea (2019) argued that land values aggregate farm and non-farm influences and the latter need to be filtered out. He developed a data set using cash rents for agricultural activity as a measure of land value specifically for farming activity. Whereas the land value model implied future losses under climate warming, the same model estimated using cash rents did not, leading the author to conclude the pessimistic results were due to using an inaccurate measure of the returns to farming activity. Bareille and Chakir (2023) assembled a large data base on farm sale prices in France for properties that sold twice between 1996 and 2019. They could replicate pessimistic results showing negative effects of warming on agricultural land values using conventional econometric modeling. But by taking advantage of the repeat sales data, which provides information on site-specific changes in land prices, they found the results reversed and implied that climate change will be very beneficial for French agriculture. The authors concluded that, taking adaptation into account, a warming climate would yield positive benefits for French agriculture that were between two and 20 times larger than had previously been estimated. On average, with full adaptation, they concluded that climate changes under the medium RCP4.5 scenario could double the value of French farmland by 2100.

A major deficiency of all these studies, however, is that they omit the role of CO₂ fertilization. Climate change as it relates to this report is caused by GHG emissions, chiefly CO₂. The econometric analyses referenced above focus only on temperature and precipitation changes and do not take account of the beneficial growth effect of the additional CO₂ that drives them. As explained in Chapter 2 CO₂ is a

major driver of plant growth so this omission biases the analysis towards underestimation of the benefits of climate change on agriculture.

10.2 Field studies of CO₂ enrichment

One of the ways the effect of CO₂ on crop growth has been studied is through “free air enrichment experiment” or FACE plots, in which small chimneys are placed in fields surrounding plants and the growth response to elevated CO₂ under varying weather conditions are recorded. Ainsworth et al. (2020) summarizes results from about 250 such studies. They found that elevation of CO₂ by 200 ppm cause an average 18% increase in crop yield in C3 plants. C4 plants exhibited benefits mainly under drought conditions.

In addition to FACE plot experiments there have been thousands of laboratory experiments on the effects of CO₂ on all kinds of plant growth. Here we review some of the results on key US agricultural crops.

Soybean

Studies on the impact of elevated CO₂ on Soybean (*Glycine max* (L.) Merr.) plants in the water-deficient region of Huang-Huai-Hai Plain, China, showed that elevated CO₂ concentrations resulted in improved photosynthesis rate, water use efficiency and growth (Li, 2013) under both normal conditions and drought conditions. The CO2Science.org website reports on 108 published experiments between 1985 and 2019 exposing soybean to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +50.9 percent. In addition there were 10 studies reporting on +600 ppm CO₂ enrichment, resulting in an average increase in photosynthesis of 90.3%.

Maize (corn)

The CO2Science.org website reports on 28 published experiments between 1983 and 2018 exposing corn (*Zea mays* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +23.7 percent. Corn also benefits from increased drought tolerance under elevated CO₂. An experimental study (Allen Jr, 2011) exposed plants to water stress conditions in sunlit controlled-environment chambers at 360 ppm (ambient) and 720 ppm (elevated) CO₂. The drought stress caused a 41% loss of growth under ambient CO₂ but only a 13% loss under elevated CO₂.

Wheat

The CO2Science.org website reports on 92 published experiments between 1983 and 2020 exposing common wheat (*Triticum aestivum* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +67.6 percent. Blandino (2020) measured the yield as well as nutritional quality of an “improver” hybrid wheat variety and its parents under elevated CO₂ levels (+166 ppm). They reported a grain yield increase of +16% but a 7% decrease in grain protein levels. But they found that the food quality of different wheat varieties responded differently to elevated CO₂ levels, so that with proper varietal selection end-users can select wheat types that best take advantage of the elevated CO₂.

Further evidence

A 2021 report from the US National Bureau of Economic Research (Taylor and Schlenker 2021) used satellite-measured observations of outdoor CO₂ levels across the United States, matched to county-level agricultural output data and other economic variables. After controlling for the effects of weather, pollution and technology the authors concluded that CO₂ emissions had boosted US crop production since 1940 by 50 to 80 percent, attributing much larger gains than had previously been

estimated using FACE experiments. They found that every ppm of increase in CO₂ concentration boosts corn yields by 0.5 percent, soybeans by 0.6 percent, and wheat by 0.8 percent.

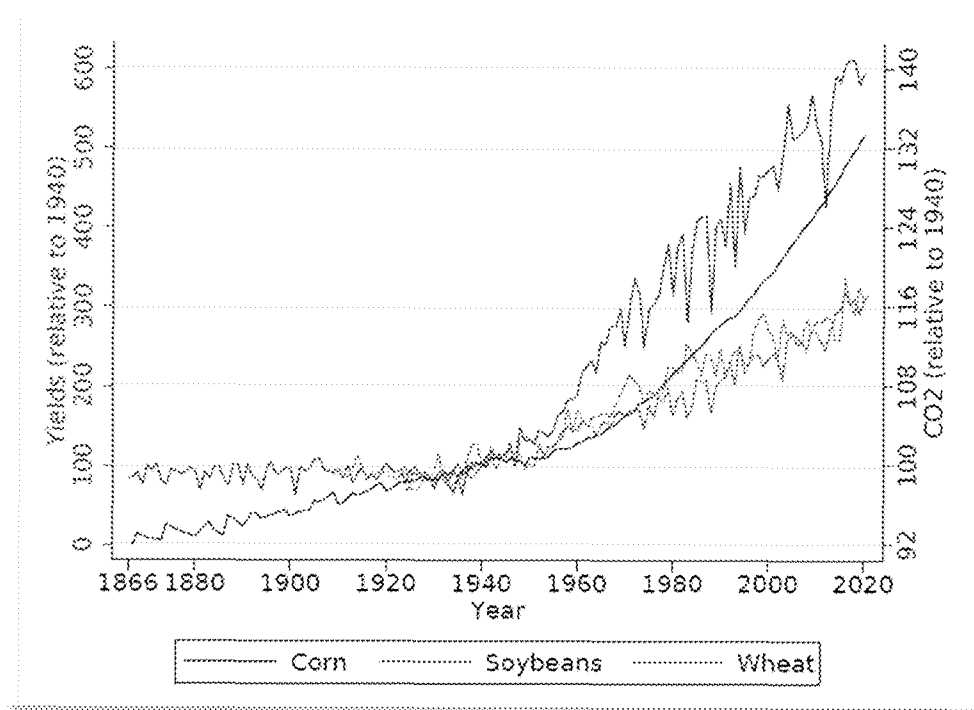


Figure 10.1: US average CO₂ levels and yields of corn, soy and wheat all normalized so 1940=100.
Source: Taylor and Schlenker (2021)

Beyond growth benefits, extra CO₂ boosts plant resilience to heat. Deryng et al. (2016) surveyed all available evidence regarding how wheat, maize, rice and soybean will grow under a combination of climate warming and rising CO₂ levels. They concluded that warming would, eventually, have a negative effect on plant growth but it would be fully compensated by the extra CO₂ for wheat and soybean, and almost fully for rice and maize. And as discussed in Chapter 2, plants use water more efficiently when there is more CO₂ in the air.

Deryng et al. (2016) surveyed evidence on crop water productivity (CWP), i.e. yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them and once it was taken into account all regions showed a net CWP gain. Deryng et al (2016) also reported that negative impacts on wheat and soybean yields were fully offset by CWP gains, and mitigated by up to 90% for rice and 60% for maize.

Similar to this, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

10.3 Crop modeling meta-analyses

Notwithstanding the abundant evidence for the direct benefits of CO₂ and of CO₂-induced warming on crop growth, in 2023 the US Environmental Protection Agency (EPA 2023) boosted its estimate of the Social Cost of Carbon (SCC) about five-fold based in large part on a very pessimistic 2017 estimate of global agricultural damages from climate warming (Moore et al., 2017). One of the two damage models used by the EPA attributed nearly half of the 2030 SCC to projected global agricultural damages based on the Moore et al. (2017) analysis. This study was a meta-analysis of crop model studies simulating yield changes for agricultural crops under various climate warming scenarios. Moore et al. projected declining global crop yields for all crop types in all regions due to warming.

McKittrick (2025) re-examined the Moore et al. database and found that, while it claimed to cover 1,722 studies, only half the entries ($N=862$) had complete records, so that the sample available for regression analysis was much smaller than both studies indicated. McKittrick noted that the variable most commonly missing was the change in ambient CO₂ and found that in many cases these could be recovered from the underlying studies or the original climate scenario tables. He thereby increased the usable sample size by 40 percent. The crop yield projections incorporating the newly available data changed considerably. As shown in Figure 10.2, whereas the partial data set implied warming would decrease yield (blue lines), the complete data set implied constant or increase global yields, even out to 5°C warming (green lines).

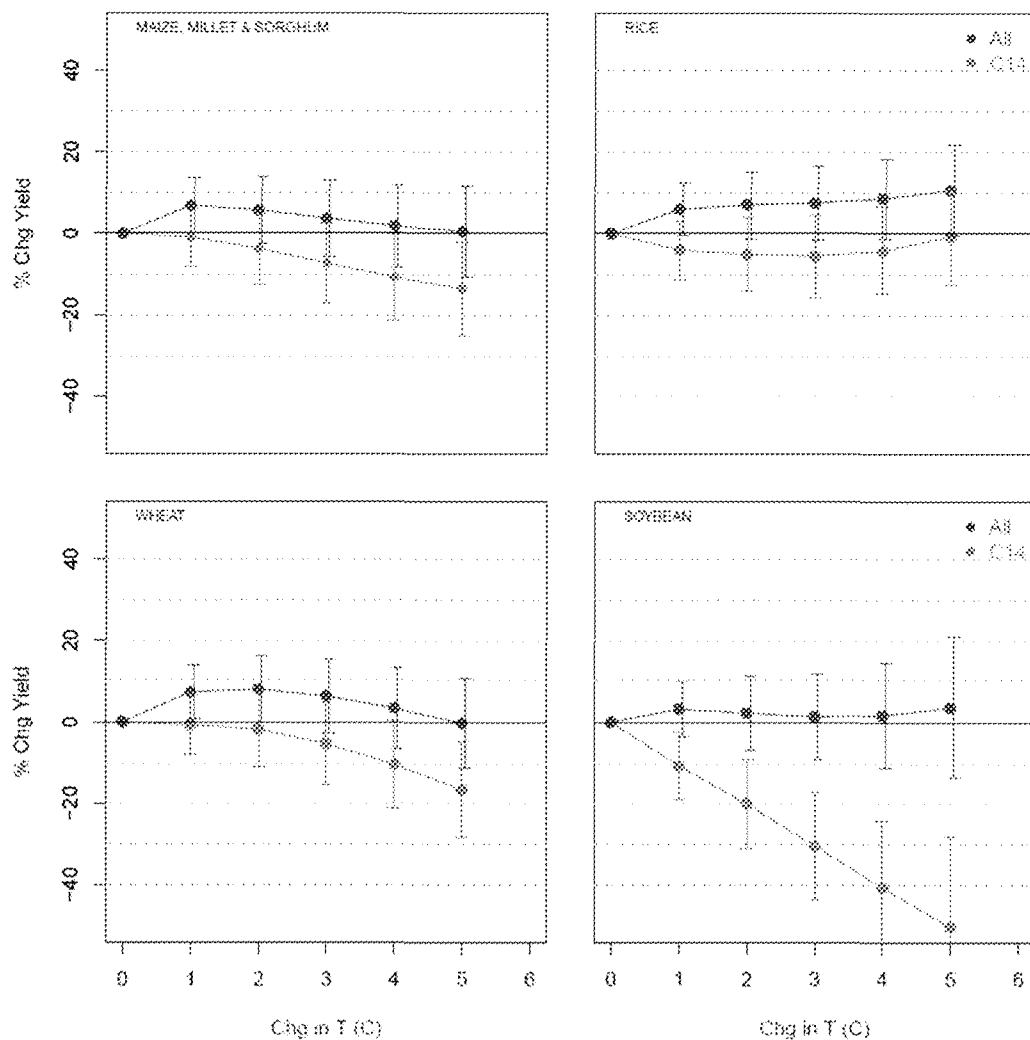


Figure 10.2 Crop yields under CO₂-induced climate warming. Blue: as published in Moore et al. (2017). Green: after including omitted data. Source: McKittrick (2025).

In summary, there is abundant evidence going back decades that rising CO₂ levels benefit plants including agricultural crops, and that CO₂-induced warming will be a net benefit to US agriculture. The warming since 1981, in combination with adaptive behaviour by farmers, has been beneficial on its own for maize. The increased ambient CO₂ has also boosted productivity of all major US crop types. Various attempts to argue that CO₂-induced warming will harm agriculture do not hold up under scrutiny.

Deschênes, Olivier and Michael Greenstone (2007) *The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather* *American Economic Review*. Feb 2007, Vol. 97, No. 1: Pages 354-385

Deschênes, Olivier and Michael Greenstone (2012) The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Reply to Comment *American Economic Review*. 102, no. 7: 3761-3773. <http://hdl.handle.net/1721.1/82641>

Ortiz-Bobea, Ariel (2019) The role of nonfarm influences in ricardian estimates of climate change impacts on US agriculture. *American Journal of Agricultural Economics*. 102 (3), 934–959.

Schlenker, Wolfram and Michael Roberts (2009) Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences* 106 (37) 15594-15598 <https://doi.org/10.1073/pnas.0906865106>

11. Managing risks of extreme weather

11.1 Socioeconomic context

Risks from human-caused climate change are convoluted with natural weather and climate variability, and are dominated by the exposure of wealth in coastal and other disaster-prone regions and vulnerabilities of poorer populations. The evolution of climate risk in the U.S. has been dominated by societal factors, rather than by changes to the actual weather and climate hazards. Deaths from weather disasters have decreased substantially since 1900, even as US population grew from 76 million in 1900 to over 331 million in 2020. For example, the Galveston hurricane killed over 8,000 people in 1900 (0.01% of the US population), whereas the worst recent disaster, Hurricane Katrina in 2005, killed 1800 people (or 0.0006% of the US population).

Technological advances have substantially reduced losses from extreme weather events. Early warning systems, satellite monitoring, and improved weather forecasting have reduced deaths, although exactly numbers are hard to quantify. <https://www.nber.org/papers/w31361> US weather forecasting has been estimated to reduce losses from weather events with an annualized benefit of \$31.5B, protecting lives, property, and supporting agriculture and transportation <https://nap.nationalacademies.org/read/12888/chapter/2> Improved hurricane forecasts have reduced pre- and post-landfall spending, with annual per hurricane cost reductions estimated at \$5B <https://www.nber.org/digest/202409/value-improving-hurricane-forecasts>

Infrastructure improvements have contributed to substantial reductions in losses from extreme weather events. Building codes, such as those implemented in Florida after Hurricane Andrew (1992) have reduced losses by ensuring structures can withstand high winds and floods. Homes built after 2002 showed minimal damage during Hurricane Michael (2018), unlike older homes. <https://www.fema.gov/case-study/role-floridas-building-codes-2018-hurricane-michael> Sea walls, like the Galveston Seawall, protect against wave action and storm surge. The New Orleans Hurricane and Storm Damage Risk Reduction System successfully mitigated storm surge during Hurricane Isaac (2012). Inland dams in the US help control flooding by storing excess water during heavy rains. It is estimated that the Tennessee Valley Authority (TVA) dams prevent about \$309M in annual flood damage in the TVA region and along the Ohio and Mississippi Rivers <https://www.tva.com/environment/managing-the-river/flood-management> During Hurricane Helene (2024), TVA's strategies prevented approximately \$406M in potential damages. <https://www.publicpower.org/periodical/article/tva-flood-mitigation-strategies-prevented-approximately-406-million-potential-damages>

11.2 Data challenges

Since 1980, NOAA has provided a count of annual U.S. weather-related disasters that it estimates to have exceeded \$1Billion (inflation adjusted), showing a substantial increase starting in 2008. NOAA and other government officials have cited the upward trend in the BDD series as evidence that climate change is making extreme weather worse (Pielke Jr.

2024). But over time, population and wealth have increased dramatically in the US, so when an extreme weather or climate event occurs, there is more damage even if there is no underlying trend in the frequency or intensity of extreme weather. A recent estimate finds that losses per weather disaster are down by about 80% since 1980, as a proportion of GDP. <https://drive.google.com/file/d/1MvgwcWaimcn1oHODqNZDG1fXF4M5Idnn/view> Pielke Jr. (2024) argued that in addition to relying on opaque data sources and unreported adjustments NOAA failed to normalize its Billion Dollar Disaster (BDD) data series properly for changes in population exposure and wealth. In May 2025 NOAA announced it has withdrawn the billion dollar disaster product from publication (Pielke Jr. 2025).

In summary, trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. And finally, the US economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages.

Pielke Jr., Roger (2024) Scientific integrity and U.S. “Billion Dollar Disasters” *NPJ Natural Hazards* 1 <https://www.nature.com/articles/s44304-024-00011-0>

Pielke Jr., Roger (2025) “RIP NOAA's Billion Dollar Disasters” Substack essay May 8, 2025 <https://rogerpielkejr.substack.com/p/rip-noaas-billion-dollar-disasters>

12 Mortality from temperature extremes

12.1 Heat and cold risks

Changes in temperature extremes are among the most certain impacts expected in a warming globe -- extreme heat events are expected to become more frequent while extreme cold events become less frequent. This pattern is evident in the historical period (as discussed in Section XX) and is expected to intensify with continued warming.

Mortality during heat extremes is typically caused by heat stroke and heat exhaustion, while mortality during cold extremes is typically caused by hypothermia and heart strain. It is well known that global mortality is substantially greater for extreme cold than for extreme heat.^{1,2}

Specific to the U.S., extreme heat and extreme cold both kill hundreds of people each year.; however, different approaches to assessing heat/cold mortality produces different results. The Center for Disease Control (CDC) National Center for Health Statistics Compressed Mortality Database, which is based on death certificates, indicates that about twice as many people die of “excessive cold” conditions in a given year than of “excessive heat.”^{3,4}

A 2015 epidemiological study of deaths in published in *The Lancet* found that cold-related deaths in the U.S. were about a factor of fifteen higher than heat-related deaths.⁵ However, the study did not adjust for the seasonal cycle in mortality rates, which tend to increase during the winter months due to non-weather factors like influenza.⁶ A more recent paper found that 86% of temperature-related deaths in the U.S. are due to cold-related mortality.⁷

¹ Qi Zhao et al., “Global, Regional, and National Burden of Mortality Associated with Non-Optimal Ambient Temperatures from 2000 to 2019: A Three-Stage Modelling Study,” *The Lancet Planetary Health* 5, no. 7 (July 2021), [https://doi.org/10.1016/s2542-5196\(21\)00081-4](https://doi.org/10.1016/s2542-5196(21)00081-4).

² <https://ourworldindata.org/part-one-how-many-people-die-from-extreme-temperatures-and-how-could-this-change-in-the-future>

³ Brett R. Scheffers et al., “The Broad Footprint of Climate Change from Genes to Biomes to People,” *Science* 354, no. 6313 (November 11, 2016): aaf7671, <https://doi.org/10.1126/science.aaf7671>.

⁴ Rachel H. Alinsky, Scott E. Hadland, J. Deanna Wilson, Pamela A. Matson, and Brendan Saloner, “Trends in Polysubstance Overdose Deaths Involving Opioids, Stimulants, and Benzodiazepines by Race and Ethnicity in the US, 2007-2021,” *JAMA Network Open* 7, no. 3 (March 2024): e238249, <https://doi.org/10.1001/jamanetworkopen.2024.8249>.

⁵ Lancet Commission on Climate and Health, “Health and Climate Change: Policy Responses to Protect Public Health,” *The Lancet* 386, no. 10006 (November 7, 2015): 1861–1914, [https://doi.org/10.1016/S0140-6736\(15\)60854-6](https://doi.org/10.1016/S0140-6736(15)60854-6).

⁶ Bob Henson, “Which Kills More People: Extreme Heat or Extreme Cold?” *Weather Underground*, January 22, 2019, <https://www.wunderground.com/cat6/Which-Kills-More-People-Extreme-Heat-or-Extreme-Cold>.

⁷ Tarik Benmarhnia et al., “Deaths Attributable to Heat and Cold: Comparison of Data Sources and Evaluation of Inconsistencies,” *GeoHealth* 8, no. 3 (March 2024): e2023GH000799, <https://doi.org/10.1029/2023GH000799>.

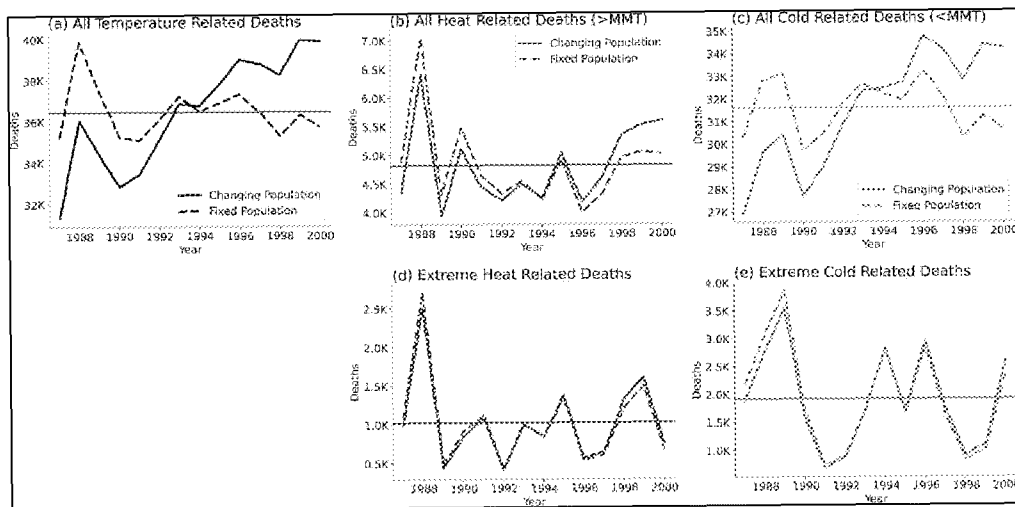


Figure 12.1: Time series of temperature-related deaths across all 106 cities. (a) The solid line represents total temperature-related deaths, while the dashed line indicates temperature-related deaths with a fixed population (average population from the 1987–2000 period). (b) Similar to (a), but for heat-related deaths. (c) Similar to (a), but for cold-related deaths. (d) Time series of deaths occurring in temperatures above the 97.5th percentile. (e) Similar to (d), but for temperatures below the 2.5th percentile. From <https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2023GH000799>

The IPCC AR6 Working Group 2 Chapter 16.2.3.5 states how heat-related mortality is declining over time:⁸

“Heat-attributable mortality fractions have declined over time in most countries owing to general improvements in health care systems, increasing prevalence of residential air conditioning, and behavioral changes. These factors, which determine the susceptibility of the population to heat, have predominated over the influence of temperature change.”

A 2011 study of 40 major US cities between 1975 and 2004, found that heat wave mortality had decreased, in spite of rising temperatures, due to adaptation.⁹ Likewise Davis et al. (2003) examined heat-related mortality in 28 U.S. cities from the 1960s to the end of the 1990s and found that heat-related mortality declined by three-quarters over the sample period. Bobb et al. (2014) examined mortality data for 106 million people in over 100 cities U.S. cities and found a 60% decline in average heat-related mortality over the period 1987–2005, from 51 per thousand deaths to 19. They furthermore found that the greatest drop was among seniors over the age of 75. In a

⁸ B. O'Neill et al., “Key Risks Across Sectors and Regions,” in *Climate Change 2022: Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, CH: Intergovernmental Panel on Climate Change, 2021), 2411–2538.

⁹ Keith T. Ingram, Carolyn W. Furman, and John W. Jones, “Climate Change Impact and Adaptation Assessment: A Guide for Coastal Resources Managers,” *Weather, Climate, and Society* 3, no. 4 (October 2011): 234–249, <https://doi.org/10.1175/WCAS-D-11-00055.1>.

study of 42 million deaths in 211 U.S. cities from 1962 to 2006. Nordio et al. (2015) found a more than 90 percent decline in the risk of mortality from excess heat.

In the context of large declines in heat-related mortality, by reducing mortality from cold events rising temperatures are associated with a net saving of lives.

It is both disappointing and telling to see how the IPCC misrepresents the situation in its AR6 Synthesis report. Section A.2.5 of that document states: “In all regions increases in extreme heat events have resulted in human mortality and morbidity (*very high confidence*).” But it is silent on the larger decline of deaths during extreme cold events.

12.2 The importance of adaptation

The observed decline in US heat-related mortality has been specifically attributed to adaptation. Wang et al. (2018) exploited the spatial variability of heatwave-related mortality across 209 U.S. cities from 1962 to 2006. While simple correlation appeared to imply an increase in mortality risk during heatwaves, accounting for adaptation to heatwave intensity caused the effect to fall to near zero and become statistically insignificant. They used the results of their epidemiological model to project heat-related mortality out to 2050 under four RCP warming scenarios (including RCP8.5) with and without adaptive behavior. Assuming people continue to adapt to the heatwave risks in the regions in which they live Wang et al. project not only no increase in heat-related mortality but an overall decrease for the US as a whole. They conclude that “Ignoring adaptation would result in a substantial overestimate of future mortality related to heat waves... Accounting for adaptation, the overall heat-related mortality by 2050 would not change substantially over time compared to 2006.”

12.3 Mortality risks and energy costs

A 2016 study of US long term mortality risks associated with temperature variations (Barreca et al. 2016) showed that increases in mortality across the US are associated both with cold weather and hot weather. But over time, the introduction of electricity and the adoption of central heating and air conditioning (AC) dramatically reduced both risks, especially those associated with hot weather. Prior to 1960, a day above 90°F (32°C) added 2.2 percent to the average mortality risk rate, but after 1960 the same weather added only 0.3 percent to mortality risk, an 85 percent reduction. Prior to 1960 temperatures below 39°F (4°C) added about 1 percent to mortality risk but after 1960 the same weather only added about half that amount. Adaptation through conventional household improvements dramatically reduced public vulnerability to weather extremes. The entire reduction in hot weather mortality was attributable to widespread adoption of indoor AC, which depended on the availability of reliable and affordable electricity.

The corollary of this finding is that the use of heating and cooling systems depends on energy being affordable. Doremus et al. (2022) showed that wealthy and poor households in the US adjust

their energy expenditures at similar rates in response to moderate temperature swings, but not in response to extreme temperature swings. When temperatures swing to very cold levels ($< 5^{\circ}\text{C}$) energy spending in high-income households rises by 1.2 percent but in low-income households by only 0.5 percent. On very hot days ($>30^{\circ}\text{C}$) electricity spending in high-income households rises by 0.5 percent but does not change at all in low-income households. The latter result is observed even in subsamples where all households have AC. The implication is that even with widespread adoption of home heating and cooling systems, inability to afford energy leaves low-income households exposed to weather extremes.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro, “Adapting to climate change: The remarkable decline in the US temperature mortality relationship over the twentieth century,” *Journal of Political Economy*, 2016, 124 (1), 105–159.

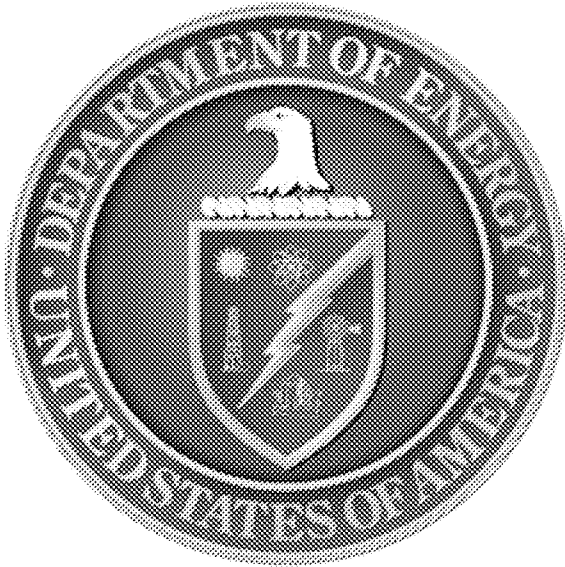
J.M. Doremus, I. Jacqz and S. Johnston (202), “Sweating the energy bill: Extreme weather, poor households, and the energy spending gap.” *Journal of Environmental Economics and Management*, doi: <https://doi.org/10.1016/j.jeem.2022.102609> .

Nordio, Francesco, Antonella Zanobetti, Elena Colicino, Itai Kloog and Joel Schwartz (2015). “Changing patterns of the temperature–mortality association by time and location in the US, and implications for climate change” *Environment International*, Volume 81, pp 80-86 <https://doi.org/10.1016/j.envint.2015.04.009>.

Wang, Yan, Francesco Nordio , John Nairn , Antonella Zanobetti and Joel D. Schwartz (2018) “Accounting for adaptation and intensity in projecting heat wave-related mortality” *Environmental Research* 161 pp. 464—471. <https://doi.org/10.1016/j.envres.2017.11.049>

Bobb JF, Peng RD, Bell ML, Dominici F. (2014) Heat-related mortality and adaptation to heat in the United States. *Environmental Health Perspectives* 122:811–816; <https://ehp.niehs.nih.gov/doi/full/10.1289/ehp.1307392>

Davis, Robert E., Paul C. Knappenberger, Patrick J. Michaels and Wendy M. Novicoff (2003) “Changing Heat-Related Mortality in the United States” *Environmental Health Perspectives* 111(14) November 2003 pp. 1712—1718.



Impacts of Carbon Dioxide Emissions on the U.S. Climate

CONFIDENTIAL DRAFT FOR DISCUSSION PURPOSES

Ad hoc Climate Working Group
United States Department of Energy
May 28, 2025

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Ad hoc Climate Working Group:

John Christy, Ph.D.

Judith Curry, Ph.D.

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SECRETARY'S FOREWORD

Over my lifetime, I have been blessed to be an energy entrepreneur in a variety of fields (nuclear, geothermal, natural gas, etc.), and I am deeply honored to serve as the Secretary of Energy under President Donald Trump. First and foremost, however, I am a physical scientist who understands that modern energy is a miracle, and I have devoted my life to bringing it to as many people as I can. Energy enables everything we do. The energy industry powers every other industry, and America's energy industry has become a global powerhouse that can supply the world's growing and advancing population.

Humanity's extraordinary development over the past two centuries is the good news. The bad news, which I've been hearing about for decades, is that today's hydrocarbon-based energy systems will lead to global decline and human suffering on a massive scale due to the existential crisis of climate change. The mainstream narrative tells us the continued use of oil, coal, and natural gas is an existential threat to humanity.

I commissioned this report to invite a more nuanced conversation. Climate change is of course a global challenge that deserves serious attention, but it is far from the most serious threat facing humanity. Although I am a nerdy guy who has always studied numbers, I understand that the art of improving the human condition requires a new framework—a clean canvas, if you will—of facts, truth, evidence, and data centered on the goal of bettering human lives.

My technical background has allowed me to read firsthand the scientific reports by the Intergovernmental Panel on Climate Change, the assessment reports by the U.S. government, and the academic climate science literature. I've been fortunate to have engaged in substantial conversations with a variety of climate scientists, including the authors of this report.

Each of the five authors has challenged and deepened my thinking on climate issues, but I did not choose them to write this assessment because we agree. In fact, I don't always agree with them, and they may not fully agree with each other. The purpose of this report is to bring about the level of sophistication, academic rigor, and integrity the climate debate deserves.

Media coverage imperfectly reflects, if not distorts, the state of the science to the point that non-experts usually have it very wrong. In many cases, science doesn't say what we think it says. To remedy the situation, I commissioned an independent team of credentialed experts to summarize the state of climate science, with particular emphasis on the question of how greenhouse gas emissions impact the United States.

I have long respected scientific integrity and so have exerted no control or influence over what the team wrote—what you are reading are their own words—not mine or anyone else's in the administration. The report relies on assessments by the United Nations, U.S. government, peer-reviewed research literature, and primary observational data.

I have scrutinized the report and met with the team to ask some tough questions about it. On that basis, I believe they've done a fine job and accurately represented the uncertainties in climate research as it exists today. Nevertheless, non-expert readers will likely be surprised by what the report says because it differs from the prevailing narrative. To my mind, that's an indictment of how severely the scientific fundamentals have been misrepresented.

Because it is so important to accurately portray the certainties and uncertainties of climate science, I am soliciting public comment on this report. Open substantial scientific debate has been sorely absent from climate science, and this is an opportunity to restore that missing element. To better human lives, we must ensure the basis for energy and environmental policymaking stands up to open-ended scientific inquiry.

The complete eradication of energy poverty is within our grasp. We are on the cusp of an era of energy dominance if we can reverse direction on energy policy. Climate change is undoubtedly a global physical phenomenon which will affect society for years to come. Allowing human ingenuity to flourish, prosper, and adapt to our changing environment will allow us to fully unleash our human potential while mitigating these risks. Holding back our energy capabilities will only depress the wellbeing of both individuals and our environment.

EXECUTIVE SUMMARY

This report reviews scientific certainties and uncertainties in how anthropogenic carbon dioxide (CO₂) emissions have affected, or will affect, the Nation's climate, extreme weather events, and selected metrics of societal well-being. Those emissions are increasing the concentration of CO₂ in the atmosphere through a complex and variable carbon cycle, where some portion of the additional CO₂ persists in the atmosphere for centuries.

Elevated concentrations of CO₂ enhance plant growth, globally "greening" the planet and increasing agricultural productivity. They also decrease ocean alkalinity by an amount within the range of natural variability. That is possibly detrimental to coral reefs, although the recent rebound of the Great Barrier Reef suggests otherwise.

Carbon dioxide also acts as a greenhouse gas, exerting a warming influence on climate and weather. The world's several dozen detailed climate models offer little guidance on how the climate responds to that influence, with the average surface warming under a doubling of the CO₂ concentration ranging from 1.8°C to 5.7°C, generally higher than simpler, data driven estimates, which suggest 1.8°C

Detailed climate models generally run "hot" in their description of the climate of the past few decades - too much warming at the surface, in the lower- and mid-troposphere, and too much amplification of warming aloft. They also produce too much recent stratospheric cooling, too much water vapor increase, too much snow loss, and too much warming in the corn belt. The combination of overly sensitive models and extreme scenarios for future emissions has exaggerated projections of future warming.

Most extreme weather events do not show long-term trends. Claims of increased frequency or intensity of hurricanes, tornadoes, floods, and droughts are not supported by historical data. Additionally, forest management practices are an often-overlooked factor in assessing wildfire activity. Global sea level has risen approximately 8 inches since 1900, but there are significant regional variations in tide gauge data driven primarily by local land subsidence; U.S. tide gauge measurements in aggregate do not show any long-term sea level acceleration.

The attribution of particular climate changes or extreme weather events to human CO₂ emissions is challenged by natural climate variability, data limitations, and inherent model deficiencies. Moreover, solar activity's contribution to the warming climate may be underestimated.

Both models and experience suggest that CO₂-induced warming may be less significant economically than commonly believed, and excessively aggressive mitigation policies could prove more detrimental than beneficial. Social Cost of Carbon estimates, which attempt to quantify the economic damage of CO₂ emissions, are highly sensitive to their underlying assumptions and so provide limited independent information.

The report supports a more nuanced and evidence-based approach to climate policy. The risks and benefits of a climate changing under both natural and human influences must be weighed against the costs, efficacy, and collateral impacts of any "climate action", taking into account the nation's need for reliable and affordable energy with minimal local pollution. Assumptions about future emissions should be grounded in reality. Climate models should be re-evaluated to address biases and uncertainties, and the limitations of event attribution studies should be clearly acknowledged. An approach that acknowledges both the potential risks and benefits of CO₂, rather than relying on flawed models and extreme scenarios, is essential for informed and effective decision-making.

INTRODUCTION: OVERVIEW AND PURPOSE OF THIS DOCUMENT

This document originated in late March 2025 when Secretary Wright assembled an independent group to write a report on issues in climate science relevant for energy policymaking, with particular focus on the question of whether carbon dioxide emissions endanger the US public. We agreed to undertake the work on the condition that there would be no editorial oversight by the Secretary, the Department of Energy, or any other government personnel. This condition has been honored throughout the process and the writing team has worked with full independence.

The group began working in early April with a deadline of May 28. The short timeline and the technical nature of the material meant that we could not comprehensively review all topics. While the report is intended to be accessible for non-experts, we have omitted some introductory or explanatory material that can easily be accessed elsewhere. Nor have we attempted to survey entire literatures related to the topics covered. We have focused as much as possible on literature published since 2020 and referenced previous IPCC and NCA assessment reports. We have also used data through 2024 where possible.

The writing team is grateful to Secretary Wright for the opportunity to prepare this report and for his support of independent scientific assessment.

May 2025

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PART I: DIRECT HUMAN INFLUENCE ON ECOSYSTEMS AND THE CLIMATE

1 CARBON DIOXIDE AS A POLLUTANT

Chapter summary

Carbon dioxide (CO₂) differs in many ways from the so-called Criteria Air Pollutants. It does not affect local air quality and has no human toxicological implications at ambient levels. It is an issue of concern because of its potential effects on the global climate, a complex issue that occupies much of this report.

The Clean Air Act of 1970 defined six so-called Criteria Air Contaminants subject to regulation (EPA, undated): particulate matter, ground-level Ozone, Sulfur Dioxide, Nitrogen Dioxide, Lead and Carbon Monoxide (CO). In 2007, the Supreme Court ruled that greenhouse gases (CO₂ among them) were also “pollutants” subject to regulation under Clean Air Act (Mass. v. EPA 2007). While the definition of “pollutant” is ultimately a legal one, there are important scientific distinctions between CO₂ and the Criteria Air Contaminants. The latter are subject to regulatory control because they cause local problems depending on concentrations that include nuisances (odor, visibility), damage to plants, and, at high enough exposure levels, toxicological effects in humans. In contrast, CO₂ is odorless, does not affect visibility and has no toxicological effects at ambient levels. It is a naturally occurring part of the atmosphere and a key component of human and plant respiration. CO₂ is essential for plant photosynthesis and higher levels are beneficial for vegetation. In these aspects, CO₂ is similar to water vapor.

Ambient outdoor air today contains about 430 parts per million (ppm) CO₂, increasing at about 2 ppm per year. The US Occupational Safety and Health Administration issues guidelines for indoor workplaces in which elevated CO₂ might be encountered, such as where dry ice is used. The Permissible Exposure Limit is 5,000 ppm over 8 hours (OSHA 2024). Allen et al. (2015) reported evidence of diminished performance on some cognitive tasks among workers in office cubicles when exposed to CO₂ levels above 1,000-1,500 ppm. These levels are far larger than any plausible ambient outdoor value through the end of the 22nd century.

The growing amount of CO₂ in the atmosphere directly influences the earth system by promoting plant growth (global greening), thereby enhancing agricultural yields, and by neutralizing ocean alkalinity. But the primary concern about CO₂ is its role as a greenhouse gas (GHG) that alters the earth’s energy balance. How the climate will respond to that influence is a complex question that will occupy much of this report.

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US Environmental Protection Agency (Undated) Criteria Air Pollutants. <https://www.epa.gov/criteria-air-pollutants> accessed April 29 2025.

US Occupational Health and Safety Administration (2024) “OSHA Occupational Chemical Database: Carbon Dioxide” <https://www.osha.gov/chemicaldata/183>

Allen, Joseph G, Piers MacNaughton, Usha Satish, Suresh Santanam, Jose Vallarino and John D.S. Spengler (2015) Associations of Cognitive Function Scores with Carbon Dioxide, Ventilation, and Volatile Organic Compound Exposures in Office Workers: A Controlled Exposure Study of Green and Conventional Office Environments. Environmental Health Perspectives 124(6) pp. 805-812 <https://doi.org/10.1289/ehp.1510037>

2 DIRECT IMPACTS OF CO₂ ON THE ENVIRONMENT

Chapter summary

CO₂ enhances photosynthesis and improves plant water use efficiency, thereby promoting plant growth. Global greening due to increased CO₂ levels in the atmosphere is well-established on all continents.

CO₂ absorption in sea water reduces the alkalinity of the oceans. The recent decline in alkalinity is within the range of natural variability on millennial time scales. Most ocean life evolved when the oceans were mildly acidic. Declining alkalinity might adversely affect corals, although the Australian Great Barrier Reef has shown considerable growth in recent years.

2.1 CO₂ and global greening

The growing CO₂ concentration in the atmosphere has the important positive effect of promoting plant growth by enhancing photosynthesis and improving water use efficiency. That is evident in the “global greening” phenomenon discussed below, as well as in the improving agricultural yields discussed in Chapter 10.

2.1.1 Measurement of global greening

“Greening” refers to an increase in the fraction of the Earth’s surface covered by plants. It can be quantified by the “Leaf Area Index” (LAI) measured by satellite. Many studies over the past decade have confirmed a global greening pattern (increase in LAI) attributable to rising CO₂ levels. Zhu *et al.* (2016) was one of the first studies to report that global greening was detectable using satellite sensors. From 1982 to 2011 they detected greening over 25-50% of the Earth versus “browning” over only 4% and attributed 70% of the greening to rising CO₂ levels (see Figure 2.1).

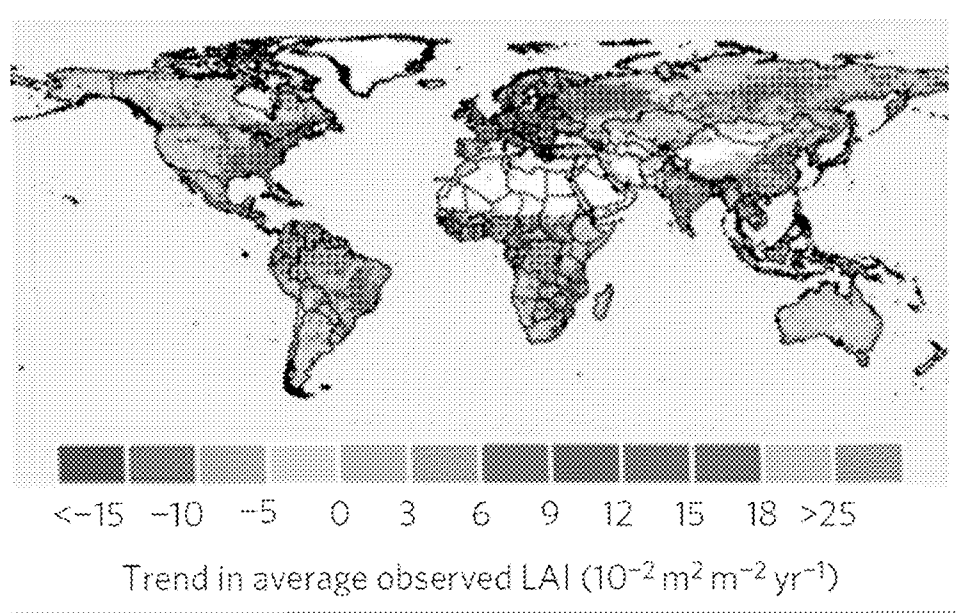


Figure 2.1: Trends in average Leaf Area Index (LAI). Source: Zhu et al. 2016 Figure 3.

Zheng (2017) confirmed the pattern, noting that greening over thirty years had added 8% to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen et al. (2019) noted that China and India were exploiting it through land management changes. Thus, while China accounts for only 6.6% of global vegetated area it accounts for 25% of global net increase in LAI. Piao et al. (2020) noted that greening was even observable in the Arctic.

While plant models predict increased photosynthesis in response to rising CO₂, Haverd et al. (2020) reported a CO₂ fertilization rate nearly double what models had predicted. That is, CO₂ fertilization had driven an increase in observed global photosynthesis by 30% since 1900, versus 17% predicted by plant models. This indicates that global models of the socioeconomic impacts of rising CO₂ have likely understated the benefits to crops and agriculture. The connection between CO₂ fertilization and climate policy will be discussed in Chapter 10.

Finally, Chen et al. surveyed claims that greening had slowed since 2000 due to drought stress. They found instead that faulty satellite sensors were the cause and that the corrected data showed accelerated greening over 55% of the globe while browning was accelerating over only 7%. In other words, the greening trend continued with no evidence of slowdown, and CO₂ fertilization remained the dominant driver

2.1.2 *Photosynthesis and CO₂ levels*

Plants build biomass through *photosynthesis*, a process that converts carbon dioxide, water, and light into sugar. The plant enzyme responsible for photosynthesis is called Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO₂ is available at the surface of the RuBisCo enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass. This is referred to as the “C3” process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth’s atmospheric CO₂ levels were usually many times higher than they are today, as shown in Figure 2.2.

About 400 million years ago CO₂ levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Berner 2006, Judd et al. 2024). Over the past 35 million years the level of atmospheric CO₂ has been steadily declining. During glaciations levels have fallen as low as 170 ppm (Gerhart and Ward 2010).

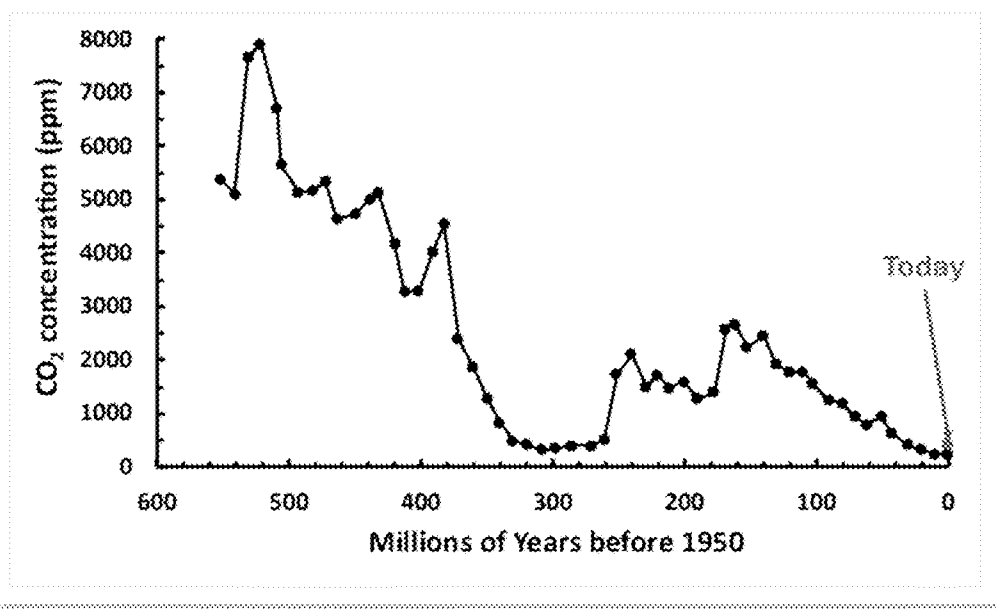


Figure 2.2. Ambient CO₂ levels over the past 550 million years. Today's concentration of 430 ppm is also shown. Source: (Berner 2006)

In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C₄, in which CO₂ is concentrated in the vicinity of Rubisco allowing for the C₃ process to function more efficiently. For agricultural purposes the plant categories are:

- C₃: rice, wheat, soybeans and most other crops
- C₄: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth rates would have declined and eventually ceased. Below 180 ppm many C₃ species experience growth rate reductions on the order of 40-60% compared to their growth rates at 350 ppm (Gerhart and Ward 2010). C₃ plants have been observed under experimental conditions to stop growing altogether at levels between 60—140 ppm CO₂. Some C₄ plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Currently, CO₂ levels are about 420 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 2.3 which is reproduced from Gerhart and Ward (2010). It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains exhibited from increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

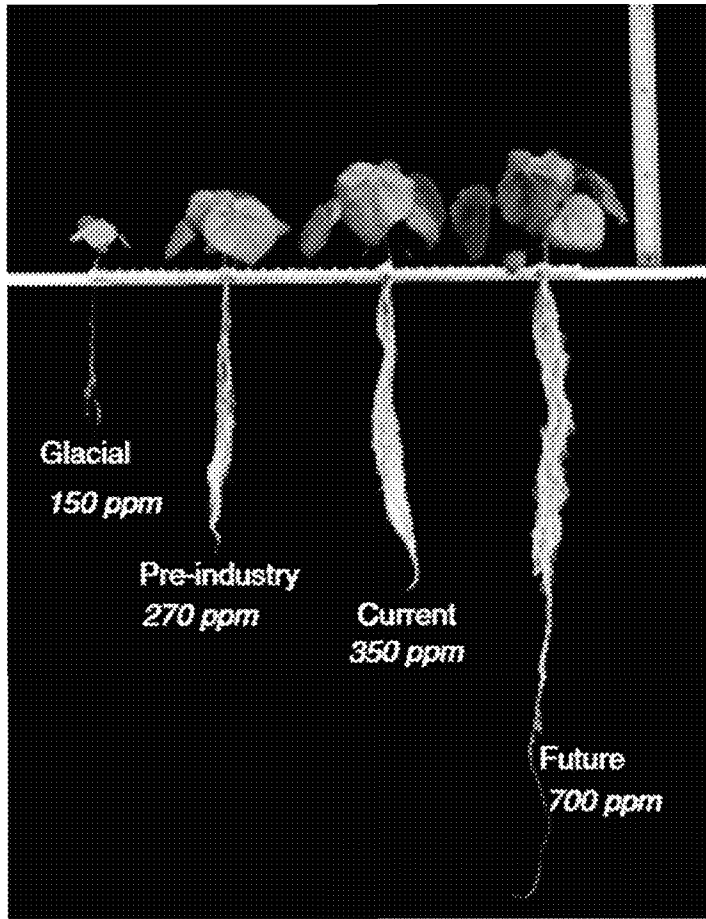


Figure 2.3: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010). Note “Current” refers to 2010 in image.

Over the past 60+ years there have been thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C₃ plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, which allows water to evaporate away. Under enriched CO₂ conditions the stomata are closed for longer periods helping the plant retain water longer, thereby increasing water use efficiency.

Specific effects of climate change on US agriculture will be reviewed in Chapter 10.

2.1.3 Rising CO₂ and crop water use efficiency

Derying et al. (2016) surveyed evidence on crop water productivity (CWP), the yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data (Free Air CO₂

Enrichment—see Chapter 10) on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them so that all regions showed a net CWP gain. Deryng et al (2016) also reported that negative impacts of warming on wheat and soybean yields were fully offset by CWP gains and mitigated by up to 90% for rice and 60% for maize.

Similarly, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

2.1.4 CO₂ fertilization benefits in IPCC Reports

The IPCC has only minimally discussed global greening and CO₂ fertilization of agricultural crops. The topic is briefly acknowledged in a few places in the body of the IPCC 6th and earlier Assessment Reports but is omitted in all Summary documents. Section 2.3.4.3.3 of the AR6 Working Group I report entitled “global greening and browning” points out that the IPCC Special Report on Climate Change and Land had concluded with *high confidence* that greening had increased globally over the past 2-3 decades. It then discusses that there are variations in the greening trend among data sets, concluding that while they have *high confidence* greening has occurred, they have *low confidence* in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports.

Overall, however, the Policymaker Summaries, Technical Summaries and Synthesis Reports fail to discuss the topic.

2.2 Ocean Alkalinity

2.2.1 Changing pH

A neutral aqueous solution has a pH of 7.0, while one with pH greater than 7.0 is basic and with pH less than 7.0 is acidic. The modern-day global average pH of sea water is estimated to be 8.04 (Copernicus Marine Service 2025), down from an estimated value of 8.2 in pre-Industrial times (Gattuso and Hansson, 2011). As CO₂ concentrations in the atmosphere increase, more is absorbed by the oceans, which decreases alkalinity. Depending upon the buffering capacity of the oceans, the oceans are expected to become somewhat less alkaline over time, consistent with the observed decrease in pH.

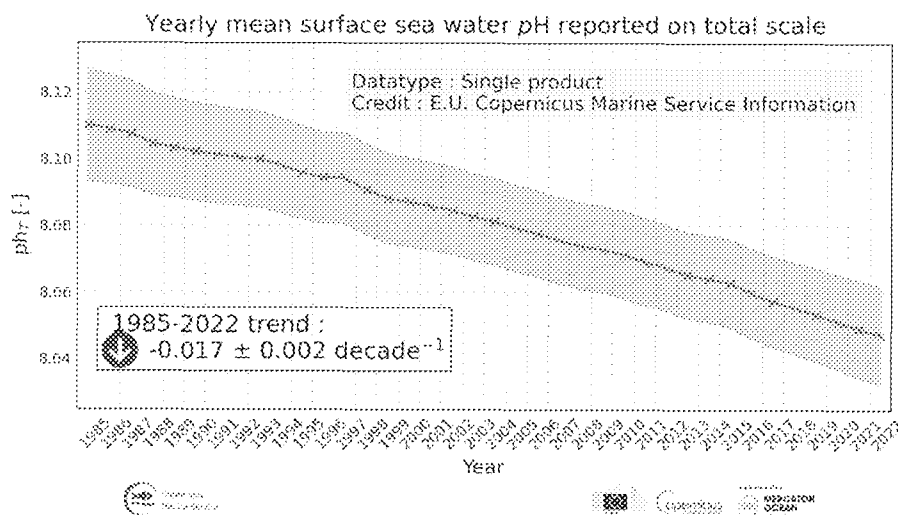


Figure 2.4: Ocean pH 1985 – 2022. Source: Copernicus Marine Service 2025

While this process is often called “ocean acidification”, it is a misnomer because the oceans are not expected to become acidic; “ocean neutralization” would be more accurate. Even if the water were to turn acidic, it is believed that life in the oceans evolved when the oceans were mildly acidic with pH 6.5 - to 7.0 (Krissansen-Totton et al., 2018). On the time scale of thousands of years, boron isotope proxy measurements of pH show that ocean pH was around 7.4 or 7.5 during the last glaciation (up to about 20,000 years ago) increasing to present-day values as the world warmed during deglaciation (Rae et al., 2018). Thus, there appears to be considerable resilience of ocean biota to natural long-term changes in ocean pH since marine organisms are exposed to wide ranges in pH anyway.

2.2.2 Coral reef changes

There are concerns that a decreasing pH of sea water will reduce the calcification rate of coral reefs. But coral reefs already endure large swings in pH, partly due to daily photosynthetic activity in the reef; measured pH values range from 9.4 during the day to 7.5 at night (Revelle and Fairbridge, 1957). De'ath et al. (2009) reported that a portion of Australia's Great Barrier Reef (GBR, the world's largest coral reef ecosystem) had experienced a 14% decline in calcification since 1990. This was tentatively attributed to increasing water temperature and decreasing pH. But Ridd et al. (2013) showed that report to have resulted from a biased data analysis which, when corrected, showed no change in calcification rates. Nevertheless, the alarm produced by the original paper has persisted as evidenced by the large number of published citations (541) received by the original study compared to only 11 citations for the correction (as of 30 April 2025).

The most recent annual summary of GBR conditions from the Australian Institute of Marine Science indicates a strong rebound has occurred in coral production (AIMS, 2023). Figure 2.5 shows the results of the AIMS surveys of hard coral cover, expressed as a percentage of the reef area. Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden et al., 2015) as well as a string of marine heatwaves, agricultural runoff and invasive species (Woods Hole 2023). Given the reported declines in GBR calcification between 1990 and 2009 and the continued increase in atmospheric CO₂ levels the rebound has come as a surprise to some observers.

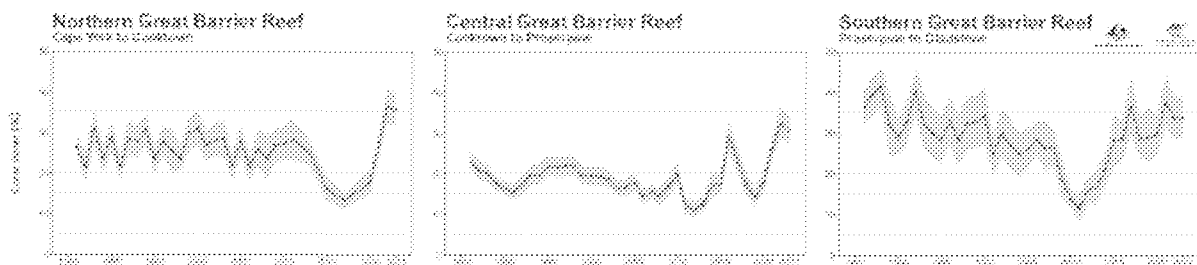


Figure 2.5 Hard coral cover of three regions of the Great Barrier Reef 1985 to 2023. Source: AIMS 2023.

It is being increasingly recognized that publication bias (alarming ocean acidification results preferred by high-impact research publications) exaggerates the impacts of declining ocean pH. An ICES Journal of Marine Science Special Issue addressed this problem with an article entitled, *Towards a Broader Perspective on Ocean Acidification Research*. In the Introduction to that Special Issue, H. I. Browman stated, “As is true across all of science, studies that report no effect of ocean acidification are typically more difficult to publish.” (Browman, 2016)

Similarly, a meta-analysis (Clements et al., 2021) of the negative effects of ocean acidification on reef fish behavior found what they called a “decline effect”: initially dramatic conclusions published in prominent journals showing apparently large reported effects of acidification tended to be followed up by subsequent studies on larger sample sizes yielding much smaller and typically non-existent effects. They call for their colleagues to improve research practices to prevent the “decline effect” from persisting:

[The] vast majority of studies with large effect sizes in this field tend to be characterized by low sample sizes, yet are published in high-impact journals and have a disproportionate influence on the field in terms of citations. We contend that ocean acidification has a negligible direct impact on fish behavior, and we advocate for improved approaches to minimize the potential for a decline effect in future avenues of research.

Clements et al. (2022)

In summary, ocean life is complex and much of it evolved when the oceans were acidic relative to the present. Much of the public discussion of the effects of ocean “acidification” on marine biota has been one-sided and exaggerated. There is a known tendency for studies reporting dramatic effects on things like coral cover and fish behavior to get published in high-impact journals and receive widespread press coverage, then subsequent research rebutting those findings receives little attention.

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3 HUMAN INFLUENCES ON THE CLIMATE

Chapter Summary

The global climate is naturally variable on all time scales. Anthropogenic CO₂ emissions add to that variability by changing the total radiative balance in the atmosphere.

The IPCC has downplayed the role of the sun in climate change but there are plausible solar irradiance reconstructions that imply it contributed to recent warming.

Climate projections are based on IPCC emission scenarios that have tended to exceed observed trends. The vast majority of academic climate “impacts” studies in recent years are based upon the extreme RCP8.5 scenario that is now considered implausible; its use as a business-as-usual scenario has been misleading.

Carbon cycle models connect annual emissions to growth in the atmospheric CO₂ stock. Models disagree over the rate of land and ocean CO₂ uptake but all agree that it has been increasing since 1959.

3.1 Components of radiative forcing and their history

3.1.1 Historical radiative forcing

A changing climate has been the norm throughout the Earth’s 4.6-billion-year history. The Earth’s temperature and weather patterns change naturally over timescales ranging from decades to millions of years. Natural variations in the surface climate originate in two ways. Internal climate fluctuations associated with circulations in the atmosphere and ocean produce exchanges of energy, water, and carbon between the atmosphere, oceans, land, and ice. External influences on the climate system include variations in the energy received from the sun and the effects of volcanic eruptions. Human activities influence climate through changing land use and land cover. Humans are also changing the composition of the atmosphere by emissions of CO₂ and other greenhouse gases and by altering the concentration of aerosol particles in the atmosphere.

The earth is warmed by the sunlight it absorbs and is cooled by the radiative heat it emits to space. Averaged over the Earth’s surface, each of these processes involve power flows of about 240 Watts per square meter (W/m²). When they are in balance, there are no net external causes of warming or cooling. Both human and natural influences on the climate alter this balance and so cause the climate to change.

Influences on the Earth’s energy balance at the top of the atmosphere are quantified by “radiative forcing”, the extent to which they disturb the warming/cooling balance; a positive forcing warms while a negative forcing cools. The IPCC’s estimated history of major components of radiative forcing since 1750 is shown in the following two figures from its AR6.

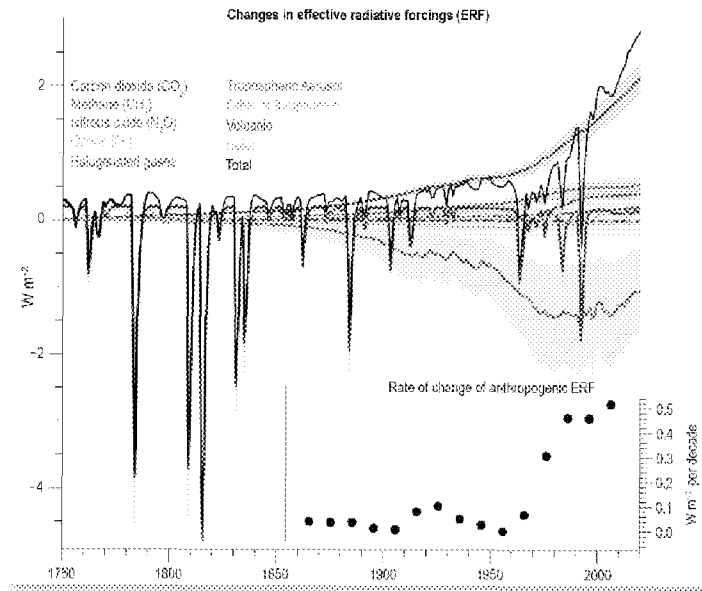


Figure 3.1.1: IPCC estimates of radiative forcing components over time. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-2/figure-2-10/>

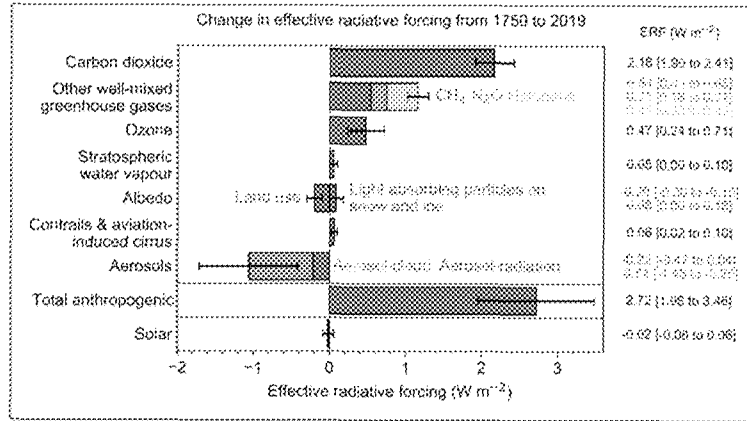


Figure 3.1.2 IPCC estimates of radiative forcing component changes from 1750 to 2019. Source: <https://www.ipcc.ch/report/ar6/wg1/figures/chapter-7/figure-7-6/>

These graphs show that the total radiative forcing is comprised of both natural and anthropogenic components. Carbon dioxide is the largest human influence on the climate and the one most relevant to the influence of energy systems. It exerts a warming influence by decreasing the cooling power of the atmosphere. Emissions of CO₂ are accumulating in the atmosphere, as described in the following section, so that the warming influence is increasing. Other greenhouse gases (methane, nitrous oxide, halogens, and ozone) act similarly, currently adding another 75% to CO₂'s warming. Aerosols exert a cooling effect, although with large uncertainties in the way they catalyze the formation of reflective clouds. As a result,

understanding the causes of recent warming requires not just identifying the warming effects of CO₂, but also the more uncertain cooling effects of aerosols.

The IPCC views the change in the radiative forcing by the sun to be negligible, based on their preference for reconstructions that imply minimal solar change since preindustrial times. Connolly *et al.* (2021) reviewed sixteen different Total Solar Irradiance (TSI) reconstructions in the literature covering the 1600-2000 interval; they vary from almost no change in TSI to a relatively large upward trend. Those authors note that the variation in TSI reconstructions combined with variations in surface temperature reconstructions allows for inferences consistent with either no or most 20th Century warming being attributable to the sun.

A particularly thorny issue is the gap in TSI data between 1989 and 1991 due to a delay in the launch of a monitor following the Space Shuttle Challenger disaster on January 28 1986. That prevented a replacement satellite from being launched in time to overlap with, and its readings to be intercalibrated with, the prior system (Zacharias 2014, Scafetta et al. 2019). This is called the ACRIM (Active Cavity Radiometer Irradiance Monitor) gap problem. The question of whether there is an upward trend in TSI over 1978 to 2018 comes down to how the ACRIM data gap is filled. Connolly et al. (2023) found that the IPCC's consensus statements on solar forcing were prematurely formulated through the suppression of dissenting scientific opinions.

The other natural radiative forcing component is largely volcanic aerosols, which exert an episodic cooling influence. Box 4.1 in the IPCC AR6 Report addresses the climate impact of volcanic eruptions, noting three explosive volcanic eruptions that occurred in the first half of the 19th century. This included the 1815 Tambora eruption that resulted in the 'year without summer', with multiple harvest failures across the Northern Hemisphere. There is uncertainty about the sign of the relatively small forcing due to the submarine volcano Hunga Tonga which erupted in 2022 (Jenkins et al. 2023, Schoeberl et al. 2024)

The anthropogenic forcing component was negligible before about 1900 and has increased steadily since, rising to almost 3 W/m² today. However, this is still only about 1 percent of the unperturbed radiation flows, making it a challenge to isolate the effects of anthropogenic forcing; state-of-the-art satellite estimates of global radiative energy flows are only accurate to a few W/m². Natural sources of global energy imbalance other than volcanoes and total solar irradiance (TSI) are not included in these graphs because they remain largely unknown.

3.1.2 Change in atmospheric CO₂ since 1958

Carbon dioxide's warming influence depends upon how much "extra" CO₂ accumulates in the atmosphere- *i.e.*, its concentration above the preindustrial value of 280 ppm. The CO₂ level as recorded at the Mauna Loa observatory in Hawaii is generally used as the representative global average concentration. The data are available online at <https://gml.noaa.gov/ccgg/trends/index.html>. The concentration was about 316 ppm at the start of the record in 1959 and is now about 430 ppm, a 36 percent increase. At the end of the last glaciation CO₂ levels had fallen to about 180 ppm. As discussed in Chapter 2 C3 plants begin dying at CO₂ levels below about 140 ppm and C4 plants at CO₂ levels below 100 ppm, so if CO₂ levels had continued falling plant life might have been in peril.

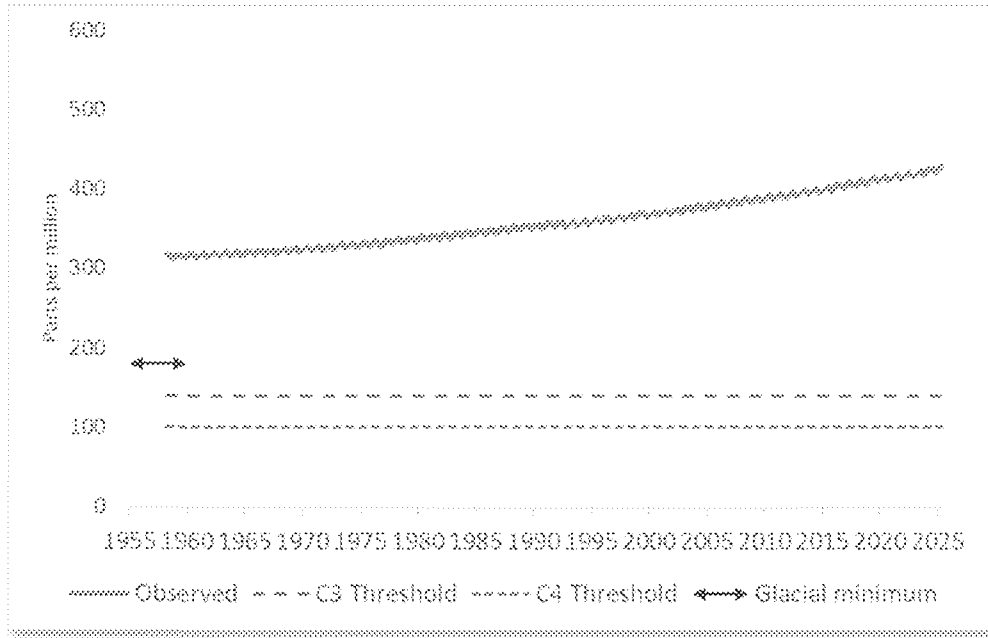


Fig. 3.1.3. CO₂: Yearly average atmospheric CO₂ concentrations (1959-2025) in ppm measured at Mauna Loa (blue). C3 Threshold: Level below which C3 plants begin dying (140 ppm, see Chapter 2). C4 Threshold: Level below which C4 plants begin dying (100 ppm, see Chapter 2). Glacial minimum: Minimum level during recent glaciations (purple arrow). CO₂ data source: <https://gml.noaa.gov/ccgg/trends/index.html>

The annual increase in concentration is only about half of the CO₂ emitted because land and ocean processes currently absorb “excess” CO₂ at a rate approximately 50% of the human emissions. Future concentrations, and hence future human influences on the climate, therefore depend upon two components: (1) future rates of global human CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere. We discuss each of these in turn.

3.2 Urbanization influence on temperature trends

Historical temperature data over land has been collected mainly where people live. This raises the problem of how to filter out non-climatic warming signals due to Urban Heat Islands (UHI) and other changes to the land surface. If they are not removed the data may over-attribute observed warming to greenhouse gases. The IPCC acknowledges that raw temperature data are contaminated with UHI effects but claims to have data cleaning procedures that remove them. It is an open question whether those procedures suffice for the purpose.

AR6 downplayed the issue by saying (WGI p. 235) that no recent evidence had emerged to alter the AR5 finding that urbanization causes an upward bias of no more than 10% in the global land surface warming trend. AR5 (WGI p. 189) also cited the 10% upper bound without citing a source. AR4 (WGI p. 244) cited Jones et al. (1990) and Peterson et al. (1999) as the basis of the claim. Peterson et al. had failed to find any difference in trends between rural and urban samples, although their definition of rural included local populations up to 10,000 persons and the relative influence of urbanization begins well below that (Spencer et al 2025). Jones et al. compared rural/urban warming in three regions: Eastern Australia, Eastern China and Western Soviet Union. Their definition of “rural” included towns of up to 10,000 in the former Soviet Union and up to 100,000 in China. They found relative warming biases greater than 10% in these

areas but conjectured that the urbanization effect averaged over the areas they did not examine would bring the global land bias to under 10% of the observed warming trend.

Prior to the IPCC AR4 several papers appeared in print arguing that the warming effect of UHIs added a relatively large (30-50%) component to observed warming and was not simulated by climate models (de Laat and Maurellis 2006, McKittrick and Michaels 2007). These findings were based on correlations between locations of maximum warming over land with locations of maximum socioeconomic development. AR4 asserted (p. 244) that these correlations were an artefact of natural atmospheric circulations and were in fact statistically insignificant, and on that basis set the findings aside. The claim attracted controversy because it was presented with no supporting evidence. McKittrick (2010) and McKittrick and Nierenberg (2010) showed that taking into account various conjectured alternative explanations for the correlations did not affect their significance. The AR5 (p. 189) conceded that the AR4 had provided “no explicit evidence” for its assessment and further acknowledged, based on these papers, that there was “significant evidence for such contamination of the record” i.e. a warming bias in the land record. However as noted, elsewhere in the report they carried forward the AR4 claim that it was less than 10% of observed warming and they expressed no caution against using the land record for climate measurement on the assumption that it is not contaminated with UHI bias. Recently Soon et al. (2023) estimated an urbanization bias in the Northern Hemisphere land record over 1850-2018 sufficient to increase the trend in the blended record from 0.55°C to 0.89°C per century.

Some studies providing evidence against UHI contamination compared warming rates between rural and urban locations (Jones et al. 1990, Peterson et al. 1999, Wickham et al. 2013). It is not known whether such methods would be capable of detecting UHI bias even when present. The influence of UHI warming is logarithmic, in other words it is strongest at low population growth levels then tapers off as local urbanization expands (Oke 1973, Spencer et al. 2025). Hence finding the same or more warming in rural areas than in nearby urban areas is consistent either with UHI bias being absent or present. McKittrick (2013) provided an empirical demonstration in which the rural/urban trends were not significantly different in a data set shown on other grounds to be contaminated with UHI bias.

Parker (2006) instead examined a sample of urban locations and found no difference in trends between subsets partitioned according to nighttime wind speed, concluding on this basis that urbanization could not be a significant factor. Here again the question is whether such a method would find UHI bias even if present. McKittrick (2013) presented an example in which UHI-contaminated data did not exhibit significant trend differences when stratified according to wind speed.

The challenge in measuring UHI bias is relating local temperature change to a corresponding change in population or urbanization, rather than to a static classification variable such as rural or urban. Spencer et al. (2025) use newly-available historical population archives to undertake such an analyses and found evidence of significant UHI bias in US summertime temperature data.

In summary while there is clearly warming in the land record, there is also evidence that it is biased upward by patterns of urbanization and that these biases are not removed by the data processing algorithms used to produce climate data sets.

3.3 Future emission scenarios and the carbon cycle

3.3.1 Emission scenarios

Because of the great uncertainties about these many factors in the decades to come, Assessing the dangers of future GHG emissions requires assumptions about what those emissions will be. Future emissions, and hence human influences on the climate, will depend upon future demographics, economic activity, regulation, and energy and agricultural technologies. Various assumptions about each of those lead

to projections of greenhouse gas emissions and concentrations, aerosol concentrations, and changes in land use, which ultimately can be combined into assumptions about anthropogenic radiative forcing.

Instead of making precise predictions of future concentrations, the IPCC has created various sets of scenarios meant to span a plausible range of possibilities for population, economy, and technologies. Recent versions of the scenarios are labeled by a number indicating the anthropogenic radiative forcing expected in 2100 under that scenario. Thus, a scenario labeled with a “6” corresponds to 6 W/m² of human-induced radiative forcing (warming) at the end of the century. (Recall current anthropogenic radiative forcing is about 2.7 W/m².)

Although the IPCC does not claim its emission scenarios are forecasts, they are often treated as such. Comparisons of past scenario groups against observations show a tendency for IPCC emission projections to overstate actual subsequent emissions. For the IPCC Third and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* was used; these were referred to as the SREP scenarios. McKittrick *et al.* (2012) showed that, when converted to per capita values, the SREP scenario emissions distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by the later analysis of Hausfather *et al.* (2019) who showed that observed atmospheric CO₂ concentrations tracked the low end of the SRES range and also of subsequent IPCC scenario ranges.

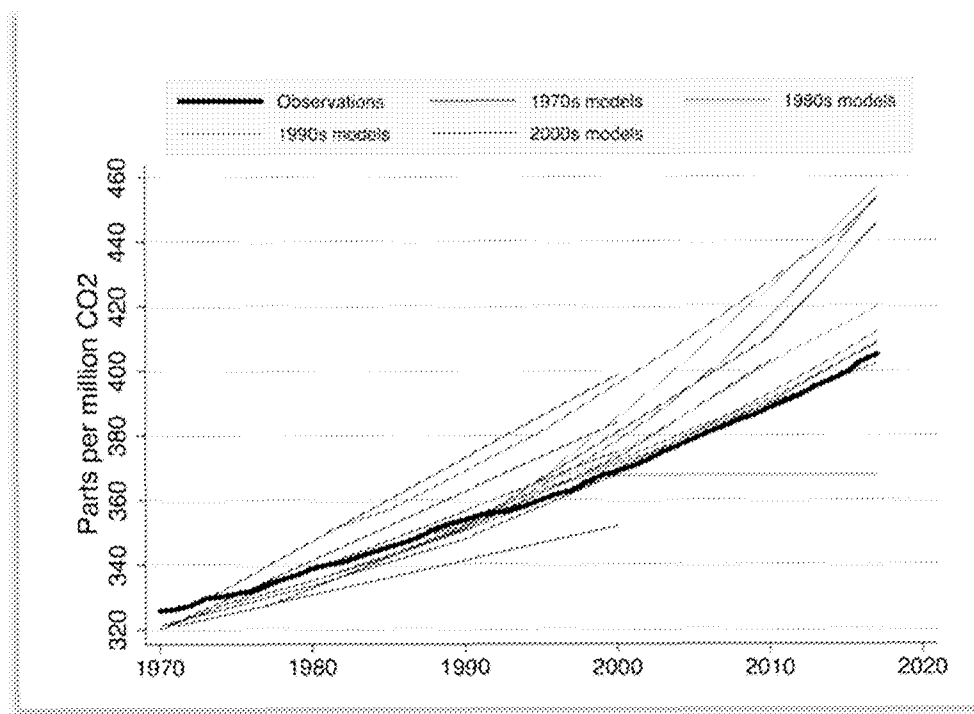


Figure 3.3.1 Comparison of observed atmospheric CO₂ levels (black line) with scenario projections (colored lines, mainly IPCC) since the 1970s. Source: Hausfather *et al.* (2019) Figure S4.

For AR5 the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCPs). These were identified by a number representing the increase in forcing and were thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying an anthropogenic radiative forcing in 2100 of

2.6 W/m²) projects a GHG concentration pathway leading to warming well below 2°C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5°C warming just in this century.

RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario in both the academic literature and popular media. It was therefore used to generate the reference outcome supposedly representing the 21st century world in the absence of increasingly stringent emission reduction policies. But RCP8.5 was intended as a low-probability high emissions scenario and its use as a business-as-usual baseline has been criticized as grossly misleading.¹ Hausfather and Peters (2020) writing in a commentary in *Nature* magazine, pointed out that RCP8.5 was developed as an extreme worst-case, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting.

The implausibility of the RCP8.5 scenario was examined by Burgess *et al.* (2021). They noted that RCP8.5 has already diverged from observed trends in energy use and the near future trends diverge sharply from those of the International Energy Agency (IEA), which provides market-based projections of energy use for the coming decades. The IEA trends, which are based on plausible extrapolations of current economic and demographic trends, run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but that even lower emission scenarios are looking unlikely.

Widespread use of RCP8.5 has created an alarmist bias in the climate impacts literature. The extent of this problem was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found that some 16,800 scientific papers published between 2010 and 2020 used the RCP8.5 scenario, with about 4,500 of the articles linking RCP8.5 to the concept of “business-as-usual”. Their analysis showed how RCP8.5 was misused not only by individual researchers, but also by influential science agencies like the IPCC and the US National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets.

Pielke and Ritchie (2020) reported new studies using RCP8.5 were published at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and “business as usual.” They conclude that the climate research community has spent a decade “committing scientific resources to science fiction” and that “The scientific literature has become imbalanced in an apocalyptic direction.”

The IPCC developed a new set of scenarios for AR6, the “Shared Socioeconomic Pathway” (SSP) scenarios, which have continued the bias shown in the RCP and SRES scenarios. Figure 3.3.2 shows total global observed CO₂ emissions compiled by the International Energy Agency (IEA) merged with the emission projection from the EIA taking account of energy use projections and current policies. The other lines show the range of IPCC SSP scenarios (SSP1-SSP5). As of 2023, global CO₂ emissions have been tracking well below SSP3 and higher.

¹ This extreme scenario is useful for modelers, since a large forcing generates a large response (warming) making it easier to assess a model’s sensitivity. But that’s very different than claiming it is a plausible future.

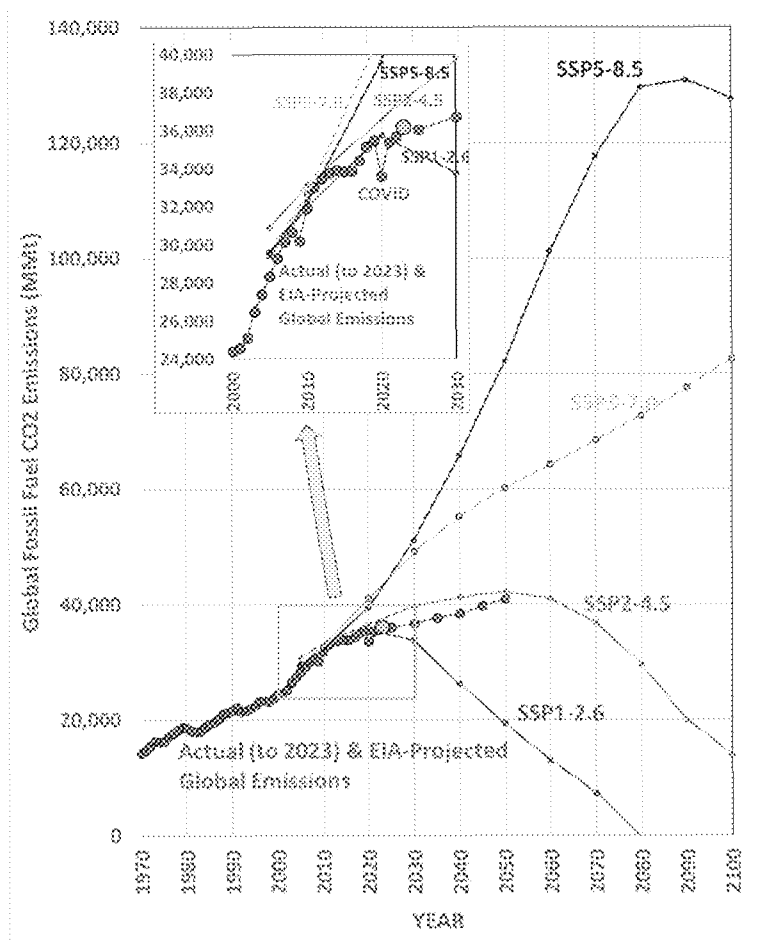


Figure 3.3.2. Observed and projected CO₂ emissions. Source: IPCC (SSP scenarios) and Energy Information Administration (EIA). Green: observed historical emissions and EIA projections. Other lines: SSP1-5. Data source: Friedlingstein et al. (2024).

3.3.2 The carbon cycle relating emissions and concentrations

Carbon dioxide emissions from fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) have led to steadily increasing CO₂ concentrations in the atmosphere, as shown in Fig. 3.1.3. The relation between emissions and concentration is determined by the global carbon cycle of land and ocean processes that exchange carbon with the atmosphere. Our understanding of these processes was reviewed by Crisp et al. (2021).

There are about 850 Gt of carbon (GtC) in the Earth's atmosphere², almost all of it in the form of CO₂. Each year, biological processes (plant growth and decay) and physical processes (ocean absorption and outgassing) exchange about 200 GtC of that carbon with the Earth's surface (roughly 80 GtC with the land and 120 GtC with the oceans). Before human activities became significant, removals from the atmosphere

² Because CO₂ is chemically transformed through the course of the carbon cycle, it is more convenient to track atoms of carbon rather than molecules of CO₂. One gigatonne of carbon (GtC) is equivalent to about 3.7 Gt of CO₂.

were roughly in balance with additions. But burning fossil fuels (coal, oil, and gas) takes carbon out of the ground and adds it to the annual exchange. That addition (together with a much smaller contribution from cement manufacturing) amounted to 10.3 GtC in 2023, or only about 5 percent of the annual exchange.

The carbon cycle accommodates about 50 percent of humanity’s small annual injection of carbon into the air by naturally sequestering it through plant growth and oceanic uptake, while the remainder accumulates in the atmosphere (Ciais et al. 2013). For that reason, the annual increase in atmospheric CO₂ concentration averages only about half of that naively expected from human emissions.

To project future CO₂ concentrations in the atmosphere, and hence future human influences on the climate, it is important to know how the carbon cycle might change in the future. The historical near-constancy of that 50% fraction means that the more CO₂ humanity has produced, the faster nature removed it from the atmosphere. That 50% fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Nino, La Nina, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert et al., 2004).

The main processes that remove excess CO₂ from the atmosphere are increased growth of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein et al., 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon (Chapter 2.1) observed by satellites since monitoring of global greenness began in the 1982.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be measured reliably. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp *et al.* (2021).

CO₂ uptake by land processes

The uptake of extra CO₂ from the atmosphere by land surface processes (as also inferred from global greening) has been modeled with 20 different dynamic global vegetation models, the outputs of which are updated every year by the Global Carbon Project (Friedlingstein, 2024). As seen in Fig. 3.3.3, all of those models agree that vegetation and soils have been sequestering carbon from the atmosphere. But we also see that the long-term trends over 1959 to 2023 (65 years) vary widely between models, by nearly a factor of 7. This demonstrates that there remains considerable uncertainty regarding how fast CO₂ from the atmosphere is being removed by land processes, which in turn translates into uncertainty regarding future atmospheric CO₂ concentrations. Those uncertain future CO₂ concentrations then imply a source of uncertainty in climate model simulations of future climate change.

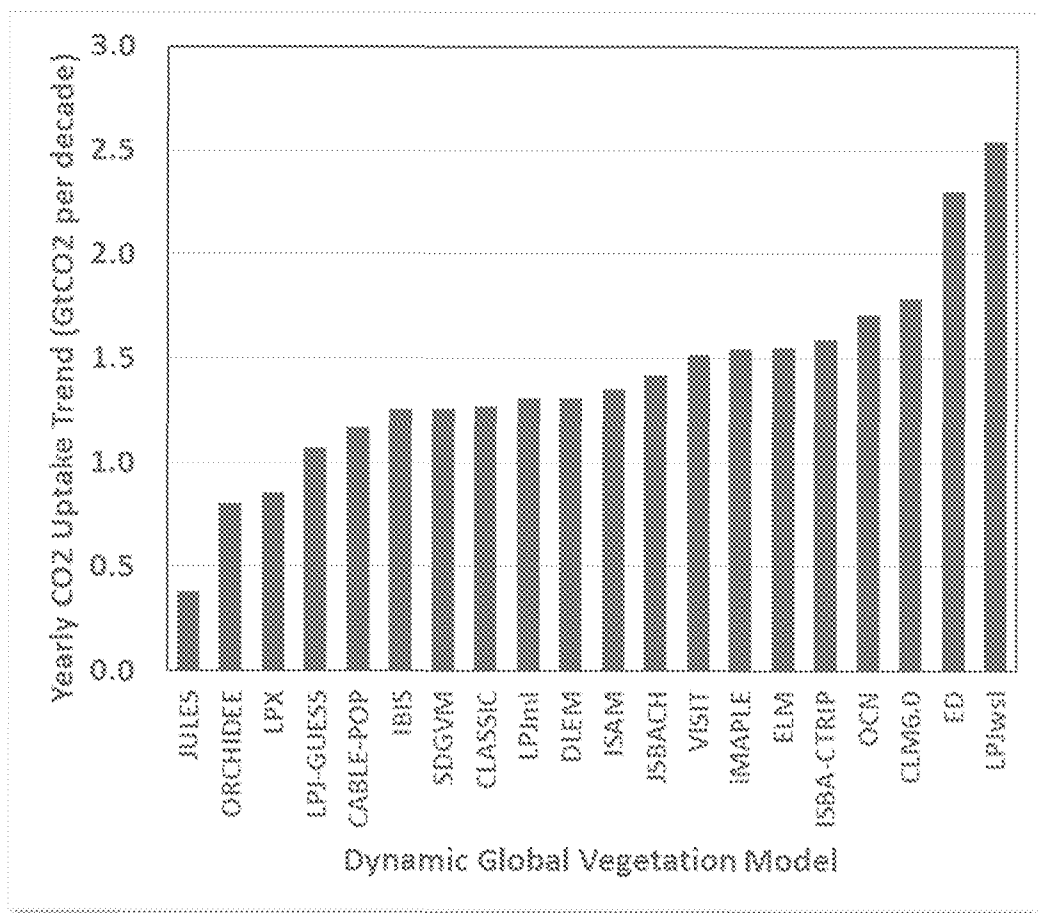


Figure 3.3.3 Decadal trends in the yearly CO₂ uptake by land processes during 1959-2023 simulated by 20 different dynamic global vegetation models periodically reported by the Global Carbon Project (Friedlingstein, 2024).

CO₂ uptake by ocean processes

The uptake of extra CO₂ from the atmosphere by ocean processes has been modeled with 10 different dynamic global vegetation models, the outputs of which are updated every year by the Global Carbon Project (Friedlingstein, 2024). Like the results from the land models, all of the ocean models agree that the global oceans have been sequestering carbon from the atmosphere at an increasing rate during 1959-2023 (Fig. 3.3.4). Unlike the land models, however, the ocean models show much better agreement with each other, with the model producing the fastest increasing CO₂ uptake being only 65% faster than the model with the most slowly increasing CO₂ uptake. Note that the average trend in CO₂ uptake across all land models in Fig. 3.3.3 is 25% larger than the average trend in ocean uptake. This suggests land processes are increasing in their ability to remove CO₂ faster than ocean processes are increasing their CO₂ sequestration.

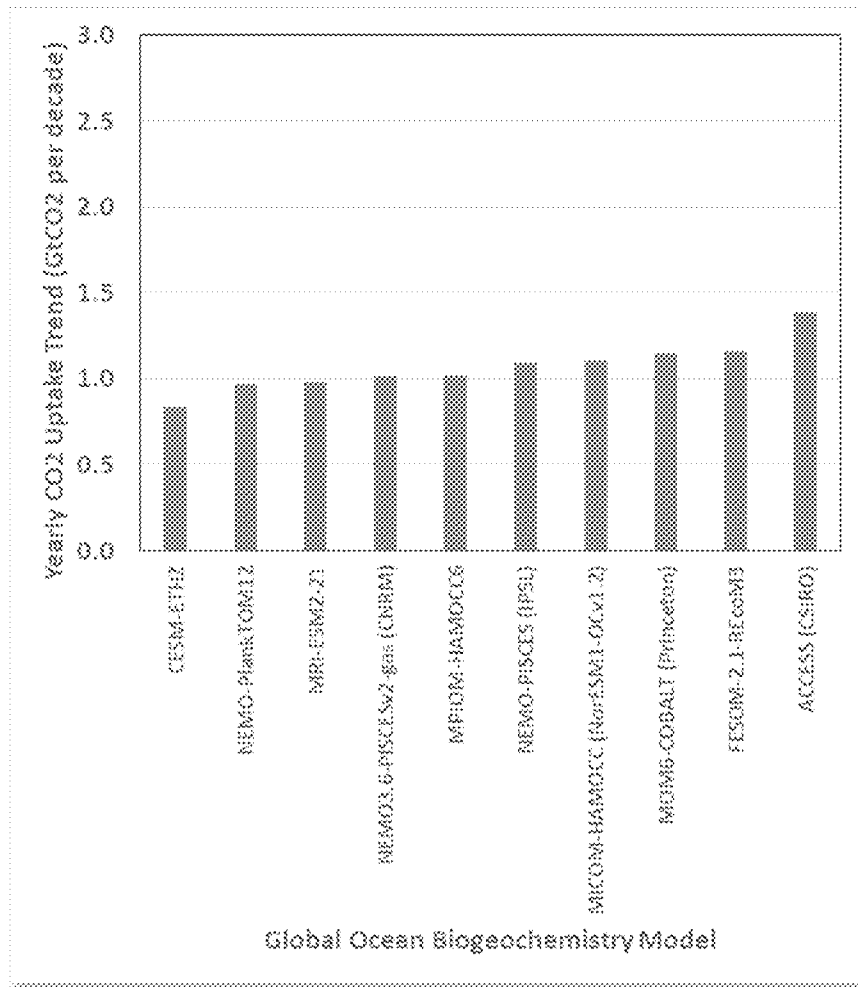


Figure 3.3.5 Decadal trends in the yearly CO₂ uptake by ocean processes during 1959-2023 simulated by 10 different ocean biogeochemistry models periodically reported by the Global Carbon Project (Friedlingstein, 2024).

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PART II: CLIMATE RESPONSE TO CO₂ EMISSIONS

4 CLIMATE SENSITIVITY TO CO₂ FORCING

Chapter Summary

There is growing recognition that climate models are not fit for the purpose of determining the Equilibrium Climate Sensitivity (ECS) of the climate to increasing CO₂. The IPCC has turned to data-driven approaches using historical data and paleoclimate reconstructions, but their reliability is diminished by data inadequacies.

Data-driven ECS estimates tend to be lower than climate model-generated values. The IPCC AR6 upper bound for the likely range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by paleoclimatic data. The IPCC AR6 lower bound for the likely range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound is more weakly justified. Evidence since the AR6 finds the lower bound of the likely range to be around 1.8°C.

4.1 Introduction

The climate’s response to increasing concentrations of CO₂ is central to the scientific debate on anthropogenic climate change, and so also to the public debate on “climate action.” The simplest measure of that response is the rise in the global average surface temperature, quantified by the Equilibrium Climate Sensitivity (ECS). ECS is defined as the amount of warming expected in response to a doubling of CO₂ from its pre-industrial concentration of 280 ppm, after all climate components have had time to adjust. Some components, like temperatures in the lower atmosphere (troposphere), adjust rapidly, while others such as the deep ocean and cryosphere might take as long as centuries. A related measure, the Transient Climate Response (TCR), better describes the shorter time scales; it is defined as the amount of warming when the CO₂ concentration is doubled by rising one percent annually for 70 years.

The 1979 Charney Report for the US National Academy of Sciences (Charney *et al.* 1979) proposed that the most likely ECS was $3.0 \pm 1.5^\circ\text{C}$. The IPCC repeatedly reaffirmed that range with only minor variations until its most recent AR6. AR5 termed 1.5 – 4.5°C as the *likely* range (66 percent probability) and stated that ECS is *extremely unlikely* (95 percent probability) to be below 1.0°C and very unlikely (90 percent probability) to exceed 6.5°C.

The uncertainty in ECS has remained stubbornly wide, despite many individual studies that claimed to narrow it. Most recently, AR6 narrowed the *likely* range to 2.5–4.0°C and deemed the *very likely* range to be 2.0 - 5.0°C. This narrowing on the low end is disputed, as will be discussed below.

Uncertainties in ECS are highly consequential for policy making. As will be discussed in Chapter 11, economic models use ECS values to project the costs of CO₂ emissions. The traditional value (3.0 °C) has typically yielded modest global social costs of CO₂ emissions, sufficient to justify some policy actions, but mostly deferred to later in this century. If ECS is very high (above 4.5°C) immediate aggressive emission controls become more imperative, whereas no CO₂ emission controls are economically justifiable for ECS below 2.0°C (Dayaratna et al. 2016, 2020). Obtaining a precise estimate is impossible, so policy making needs to account for the uncertainty.

4.2 Model-based estimates of climate sensitivity

The ECS ranges given in IPCC AR4 and AR5 were obtained primarily by examining the behaviour of large-scale climate models, also called General Circulation Models (GCMs). However, the IPCC changed

course in its AR6 when it turned to a more direct data-driven methodology. Here we discuss some of the pitfalls of using GCMs to try to determine the Earth’s climate sensitivity.

ECS is an emergent property of climate models—that is, it is not directly parameterized or tuned. Historically, collections of parameterizations have been chosen to produce an expected value of climate sensitivity, particularly with regards to sub-grid-scale cloud processes, particularly in AR4 and to a lesser extent in AR5. Otherwise plausible GCMs and parameter selections have been discarded because of perceived conflict with this warming rate, or aversion to a model’s climate sensitivity being outside an accepted range. For example, even in a CMIP6 model, Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute climate model (emphasis added):

“We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming; an endeavor which has clearly been successful. Due to the historical order of events, the choice was to do this practically by *targeting an ECS of about 3 K using cloud feedbacks*, as opposed to tuning the aerosol forcing.”

In other words, the modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

Direct warming from CO₂ doubling is only about 1°C (Hall and Manabe 1997); further warming arises from climate feedbacks that are not explicitly resolved by the GCM but rely on parameterizations of physical processes. Higher values of ECS arise primarily from assumed positive cloud feedbacks, whereas the magnitude and even the sign of the feedbacks are very uncertain. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle (Curry and Webster, 1999). It is difficult for GCMs to simulate any of these processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks.

ECS can be determined from climate model simulations by doubling the concentration of CO₂ and allowing several centuries for the warming to equilibrate. To avoid the necessity of long simulations, “effective climate sensitivity” is commonly evaluated from a 150-year simulation in response to a sudden quadrupling of CO₂.

The spread of ECS values from the CMIP5 ensemble of climate models used in the AR5 was 2.0–4.7°C; that range increased for the CMIP6 models used in the AR6 to between 1.8 and 5.7°C (Chen et al, 2021, Scaffeta 2021, see Figure 5.1). Far from settling the model-based sensitivity of climate system uncertainties appear to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models (Zelinka et al., 2020)

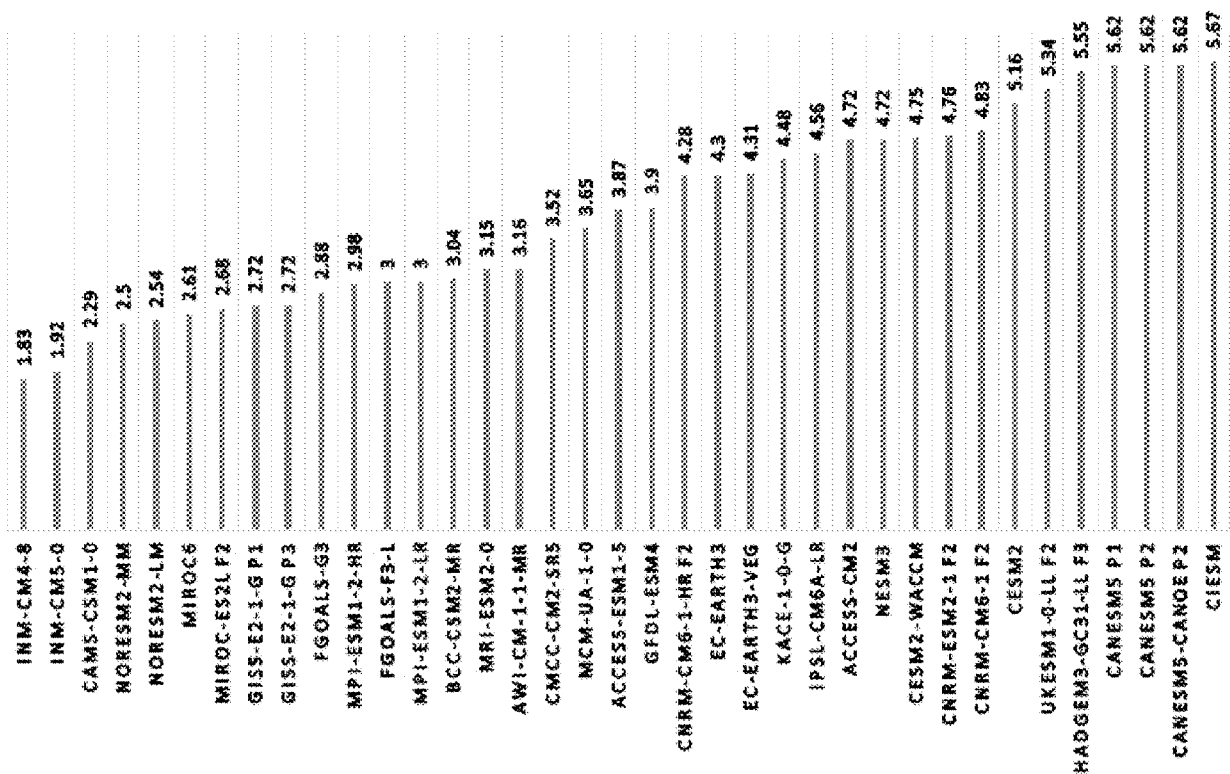


Figure 4.1 Equilibrium Climate Sensitivities in °C of 37 climate models from the CMIP6 ensemble. Identifiers for the various models appear along the horizontal axis. From (Scafetta, 2021) <https://www.mdpi.com/2225-1154/9/11/161>

Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6 (2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying instead on other methods, chiefly a recent empirical estimate.

4.3 Data-driven estimates of climate sensitivity

Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes, aerosols) have changed in the past (Otto et al., 2013). Using this information, a simple empirical model called an Energy Balance Model can be employed. It requires estimating a feedback parameter whose uncertainties are highly amplified in the resulting ECS (Roe and Baker, 2007).

The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and the ocean data is inadequate. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling, or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects need to be estimated to isolate the warming effect of CO₂. Over time, the IPCC's estimate of the cooling effect of aerosols has declined (Lewis 2022).

Paleoclimate proxies are also used to evaluate the sensitivity of past climates, by comparing paleoclimate changes in the Earth’s temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today. The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states may not be representative of the current state of the climate system.

A recurring theme in the climate literature is that ECS estimates based on historical data are smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). About 15 estimates based on historical data appeared in the peer-reviewed literature between 2012 and 2024 yielding ECS best estimates between 1.0°C and 2.5°C, although critics have questioned some of the methods and the data quality. For the AR6, the IPCC placed primary weight on the results of Sherwood et al. (2020) that combined historical and paleoclimate proxies and yielded a best estimate of 3.1°C. Lewis (2022) raised a number of concerns about this result, including methodological errors, outdated input values, and use of subjective versus objective Bayesian priors in the analysis. Lewis’ analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood et al. analysis – median 2.2°C (1.8–2.7°C in the 17–83 percent *likely* range, and 1.6–3.2°C in the 5–95 percent *very likely* range). The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis estimated it to be over 50 percent. The most recent publications on the debate between Sherwood et al. and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

An argument emphasized in AR6 is that data-driven ECS estimates might understate the future warming response to GHGs because of a so-called “pattern effect” (Forster et al 2021). The tropical Pacific is believed to strongly influence the overall efficiency with which the Earth radiates heat to space, but some regions remove heat more efficiently than others. If the west-to-east temperature gradient in the tropical Pacific is weakened in a warming climate, warming would concentration where heat is less efficiently removed, raising ECS.

Most climate models simulate that rising GHGs will weaken the east-west temperature gradient, which led the IPCC in the AR6 to conclude that data-driven ECS estimates understated the *future* ECS value. However, Seager et al. (2019) pointed out that, contrary to models, the east-west temperature gradient has been strengthening over time. They further argued that the mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic dynamics and there is no reason to expect the gradient to weaken. A similar argument was recently made by Lee et al. (2024), who concluded that “the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere”; in other words, GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate may be *lower* than current estimates.

4.4 Transient Climate Response

The Transient Climate Response (TCR) provides a more useful observational constraint on climate sensitivity. TCR is the amount of warming that results when CO₂ is increased at an annual rate of 1 percent over a period of 70 years (i.e., doubled gradually). Relative to the ECS, observationally determined values of TCR avoid the problems of uncertainties in ocean heat uptake and the fuzzy boundary in defining equilibrium arising from a range of timescales for the longer-term feedback processes (e.g., ice sheets). TCR is more generally related to peak warming and better constrained by historical warming, than ECS. IPCC AR6 judged the *very likely* range of TCR to be 1.2–2.4°C. In contrast to ECS, the upper bound of TCR is more tightly constrained. For comparison, the TCR values determined by Lewis (2023) are 1.25 to

2.0°C, showing much better agreement with the AR6 values than was seen in a comparison of the ECS values.

As will be discussed in Chapter 6, a real-world ECS smaller than the model average is supported by studies that show climate models on average overestimate the observed surface and troposphere warming over the past 50 years. Lower sensitivities also align with evidence from consistent fingerprinting (Section 8), where model responses need to be downscaled to align with observed trends.

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